Autonomy: From Deep Space to Inner Space

Kanna.Rajan@mbari.org

Principal Researcher for Autonomy

Monterey Bay Aquarium Research Institute (MBARI)

Moss Landing, California

http://www.mbari.org/autonomy/

Funded by the David and Lucile Packard Foundation

Outline

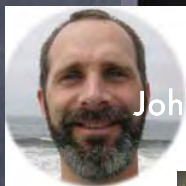
- Introduction
  - Issues in Ocean Observation
  - MBARI - brief intro
  - Scientific Motivation
  - Background - Autonomy & Legacy & Lessons
- Partitioned Interleaved Planning and Execution (and state Estimation)
- Field Results
- Next Steps - CANON

Collaborators

Frederic Py: Autonomy

Sergio Jiménez Celorrio: Learning/Madrid

Jnaneshwar Das: Adaptive Sampling /USC

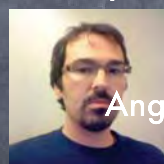


John Ryan: Biological Oceanography

Thom Maughan: Project Mgr and Sampling

Julio Harvey: Molecular Ecology

Robert Vrijenhoek: Ecology



Angel Olaya: Adaptive Sampling/Madrid

Gaurav Sukhatme: Robotics and Adaptive Sampling/USC

Maria Fox: Model Learning/Strathclyde

On Ocean Observation

Most of the previous century could be called a "century of undersampling."

Walter Munk

Secretary of the Navy Research Chair in Oceanography, Scripps Institute of Oceanography, UCSD

Testimony to The U.S. Commission On Ocean Policy, 18 April 2002

On Planning

In preparing for battle I have always found that plans are useless, but planning is indispensable.

&

Failing to plan is planning to fail.

General David Dwight G. Eisenhower, Supreme Commander Allied Forces, WWII
and
34th President of the United States

On Automation

"We should…send machines and instruments out to sea, not people…"

David Packard
MBARI Founder
Co-Founder Hewlett-Packard
&
United States Under-Secretary of Defense,
Reagan Administration

On Automation

"We should…send machines and instruments out to sea, not people…"

David Packard
MBARI Founder
Co-Founder Hewlett-Packard
&
United States Under-Secretary of Defense,
Reagan Administration

Key Problems in Ocean Observing

- Tools and techniques are inadequate to understand dynamics of coastal ocean processes
  - ✦ "*We've been doing Oceanography the way Darwin did more than a 100 yrs ago. We need new tools and techniques to better characterize our environment, especially the oceans*" Marcia McNutt, ex-MBARI President/CEO, now Dir. US Geological Survey/Science Advisor Sec. of Interior
- Often the phenomenon to be observed, cannot be sampled directly
  - ✦ Use proxy variables (e.g Chl. Fluorescence, backscatter, temperature, salinity)
- Obtaining power & comms. in the water-column is difficult/non-existent
- Synthetic ocean models are poor predictors of change
- Persistence presence necessary to understand spatio-temporal variation
- Sub-sampling the large ocean is expensive and unsustainable
  - ✦ Ship and labor costs are going up
  - ✦ Large expeditions with multiple ships/crews are logistically difficult
  - ✦ Oceanographers prefer "Terra firma"

Why is Ocean Sciences interesting....now?

- Multi-disciplinary in nature
  - Physicists, Chemists, Mechanical, Civil, Electrical Engineering, Biological, Physical, Chemical Oceanographers, Environmental Engineering, Computer Science, Economists, Numerical Analysts…
- At a cusp:
  - Realization that the Oceans are regulators for Global Climate processes
    - Synoptic views, not point data can tell us how ocean processes actually work
  - Realization of possible anthropogenic influences on our environment and the impact to the oceans
  - Advances in sensors, platforms, robotics, control, AI are substantial over ~40 years
  - Large science is slowly coming to the fore in Oceanography
    - E.g NSF funded $350 M Ocean Observatory Initiative (OOI)
      - Global/Coastal/Regional Cabled Observatories proposed

Does a domain matter?

Space

- Power is not such a big deal (payload scaling is the issue)
- Observability is by and large not such a big deal
- Communication is generally not a problem given observability
- Reachability is definitely an issue
- Launch costs are disproportionally high
- But space has substantial funding
  - embedded in the public's imagination

The Oceans

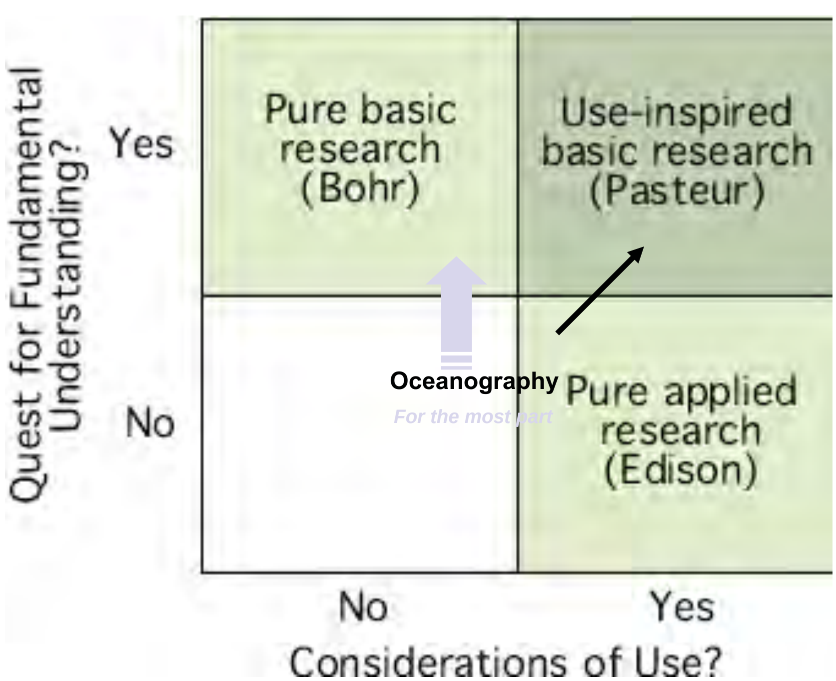
- Power *is* a big deal; you have to carry it with you
- Observability is fundamentally lacking
- Communication is a huge problem given lack of observability
- Reachability is not as much an issue given a support vessel
- Launch costs are disproportionally high
- Marine science/engineering has nowhere near as much resources

MBARI:Why is it unique?

- Privately funded
  - By the David and Lucille Packard Foundation
  - Dependence on Congress is minimal for for its operation
  - By its charter < 25% of its internal budget for external (NSF, NASA, ONR) monies
- Long term view of Ocean Science and Engineering is *strongly* encouraged
- Strong applied technology focus for *inter-disciplinary* science
- Science, Engineering and Operations are in-house
- Scientists and engineers (mostly) free from undue management & budgetary interference
  - MBARI's influence in the Ocean sciences in the US is disproportionate to its size
- A strong desire to make an impact in Oceanographic sciences by *sharing and collaborating* with external entities

MBARI: What niche does it occupy?

Pasteur's Quadrant



~200 Staff
- Science
- Engineering
- Operations
- Outreach

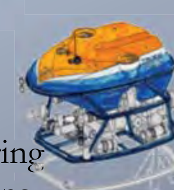
12 Principal Scientists

(Biology, Chemistry, Ecology, Genetics, Sensors, Platforms, Autonomy)

Deep-dive ROVs,
Test Tank
AUVs & ships
Moorings & buoys

Annual Budget ~$40M

Funded by the David & Lucille Packard Foundation



~200 Staff
- Science
- Engineering
- Operations
- Outreach

12 Principal Scientists

(Biology, Chemistry, Ecology, Genetics, Sensors, Platforms, Autonomy)

Deep-dive ROVs,
Test Tank
AUVs & ships
Moorings & buoys

Annual Budget ~$40M

Funded by the David & Lucille Packard Foundation

Autonomy: Outer to Inner Space *Kanna Rajan,* MBARI *2010*
Friday, December 10, 2010

The MBARI Fleet

~200 Staff
- Science
- Engineering
- Operations
- Outreach

12 Principal Scientists

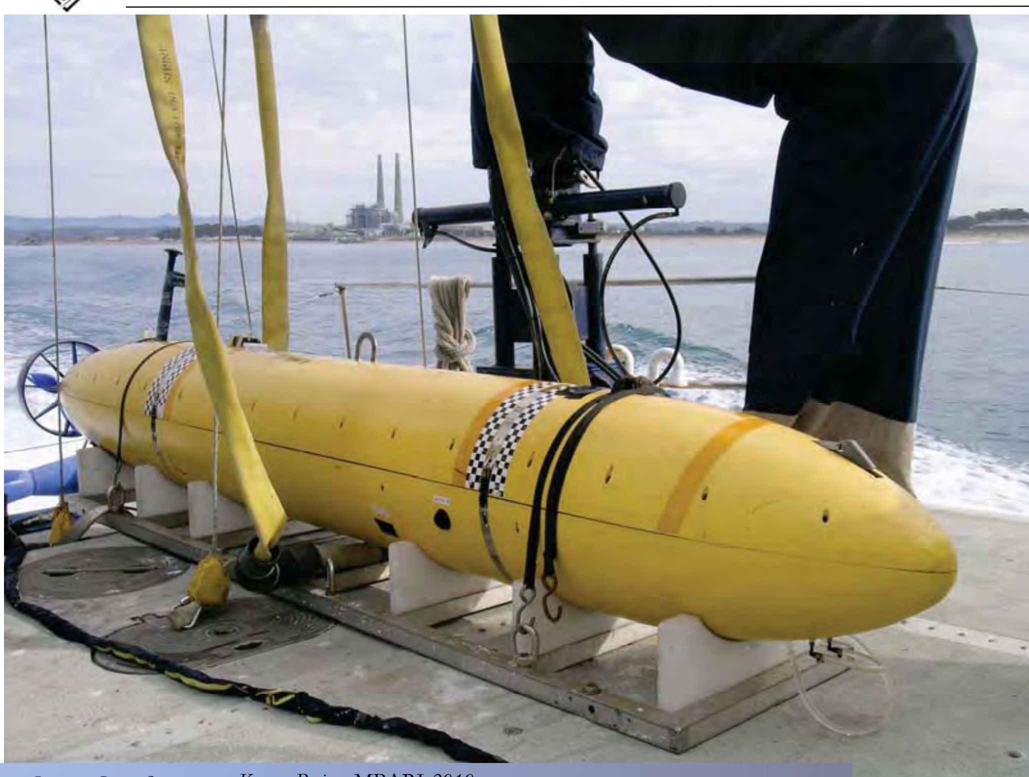
(Biology, Chemistry, Ecology, Genetics, Sensors, Platforms, Autonomy)

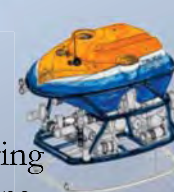
Deep-dive ROVs,
Test Tank
AUVs & ships
Moorings & buoys

Annual Budget ~$40M

Funded by the David & Lucille Packard Foundation

The MBARI Fleet





~200 Staff
- Science
- Engineering
- Operations
- Outreach

12 Principal Scientists

(Biology, Chemistry, Ecology, Genetics, Sensors, Platforms, Autonomy)

Deep-dive ROVs,
Test Tank
AUVs & ships
Moorings & buoys

Annual Budget ~$40M

Funded by the David & Lucille Packard Foundation

The MBARI Fleet

~200 Staff
- Science
- Engineering
- Operations
- Outreach

12 Principal Scientists

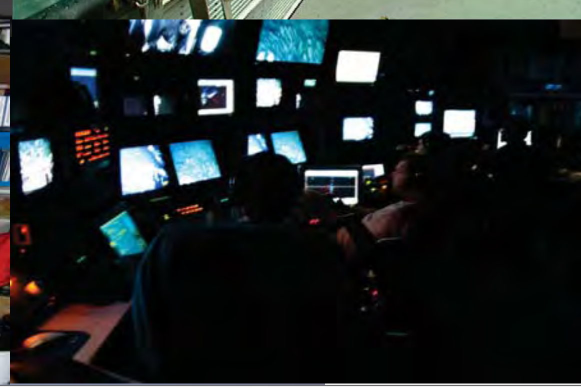
(Biology, Chemistry, Ecology, Genetics, Sensors, Platforms, Autonomy)

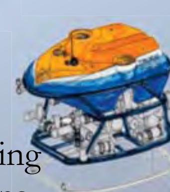
Deep-dive ROVs,
Test Tank
AUVs & ships
Moorings & buoys

Annual Budget ~$40M

Funded by the David & Lucille Packard Foundation

The MBARI Fleet





~200 Staff
- Science
- Engineering
- Operations
- Outreach

12 Principal Scientists

(Biology, Chemistry, Ecology, Genetics, Sensors, Platforms, Autonomy)

Deep-dive ROVs,
Test Tank
AUVs & ships
Moorings & buoys

Annual Budget ~$40M

Funded by the David & Lucille Packard Foundation

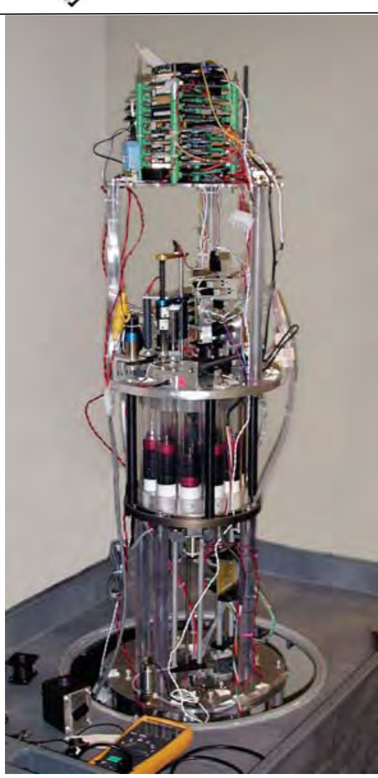
And then the unique Platforms…:ESP

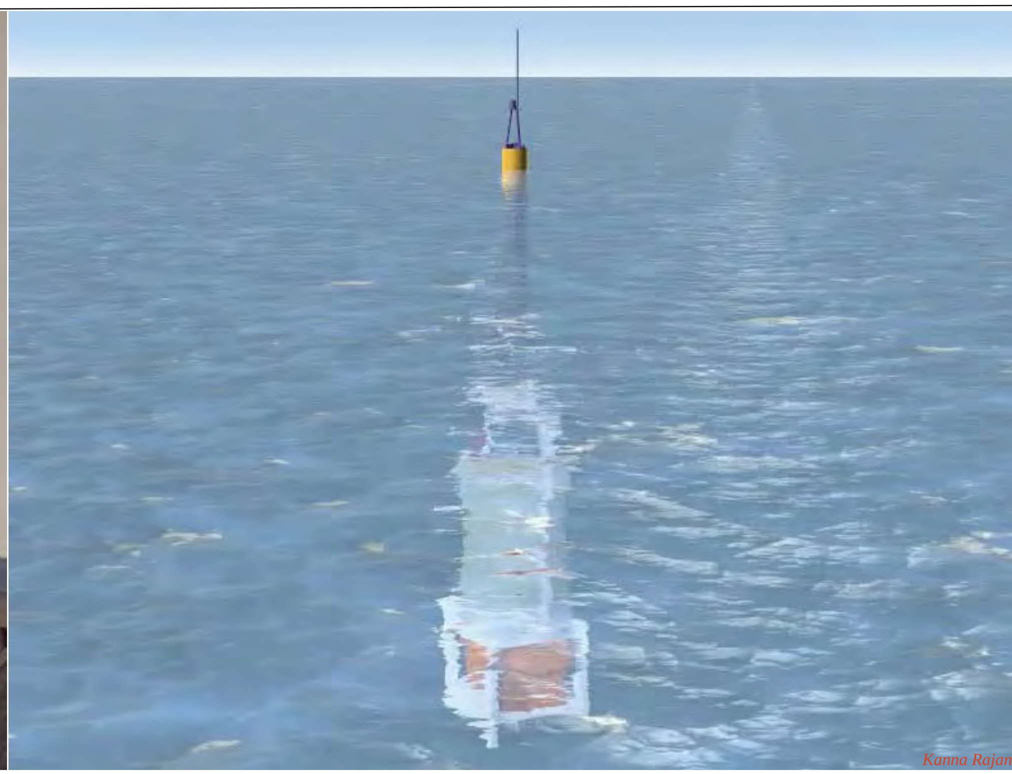
Courtesy Chris Scholin, MBARI

Kanna Rajan 2009

Friday, December 10, 2010

And then the unique Platforms…:ESP



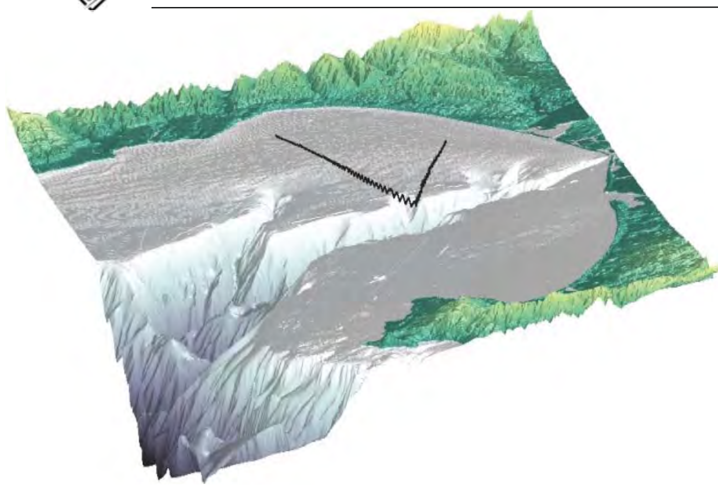


Courtesy Chris Scholin, MBARI

Kanna Rajan 2009

Friday, December 10, 2010

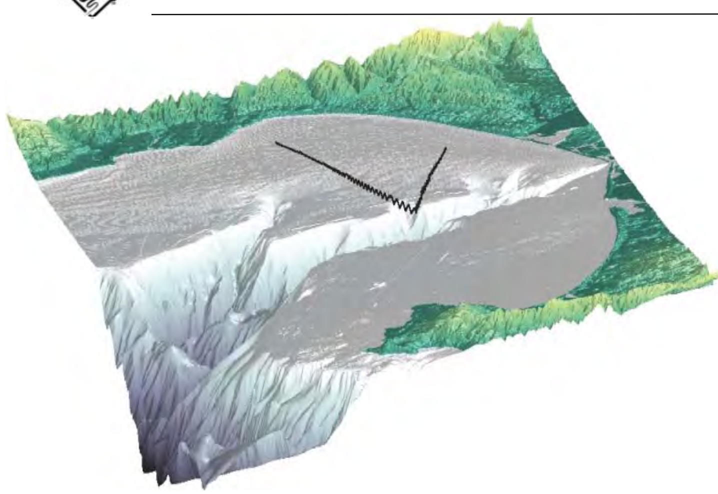
Focus of Interest: Event Response for Coast Ocean Processes

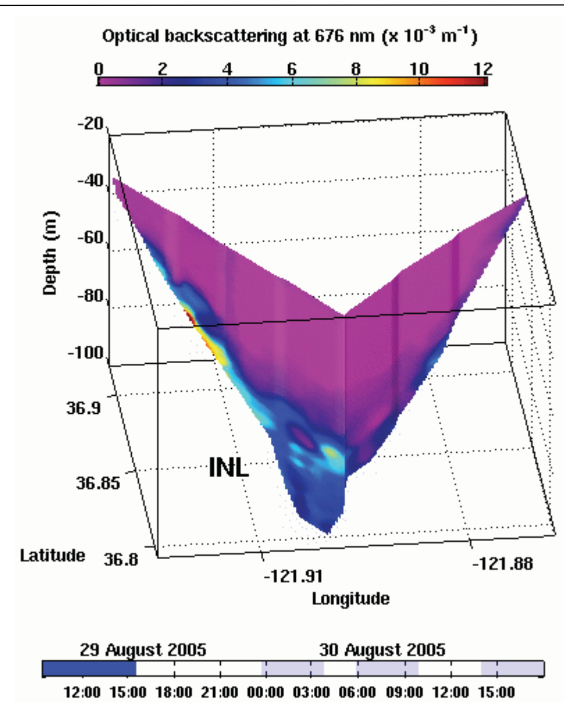


Intermediate Nepheloid Layers (INLs)

- Fluid sheets of *suspended particulates*. Originate from the *sea floor* through diverse fluid dynamics [McPhee-Shaw 2004].
- Large Horizontal Scales (Kms)
- Small Vertical Scales (meters)
- Patchy

Focus of Interest: Event Response for Coast Ocean Processes

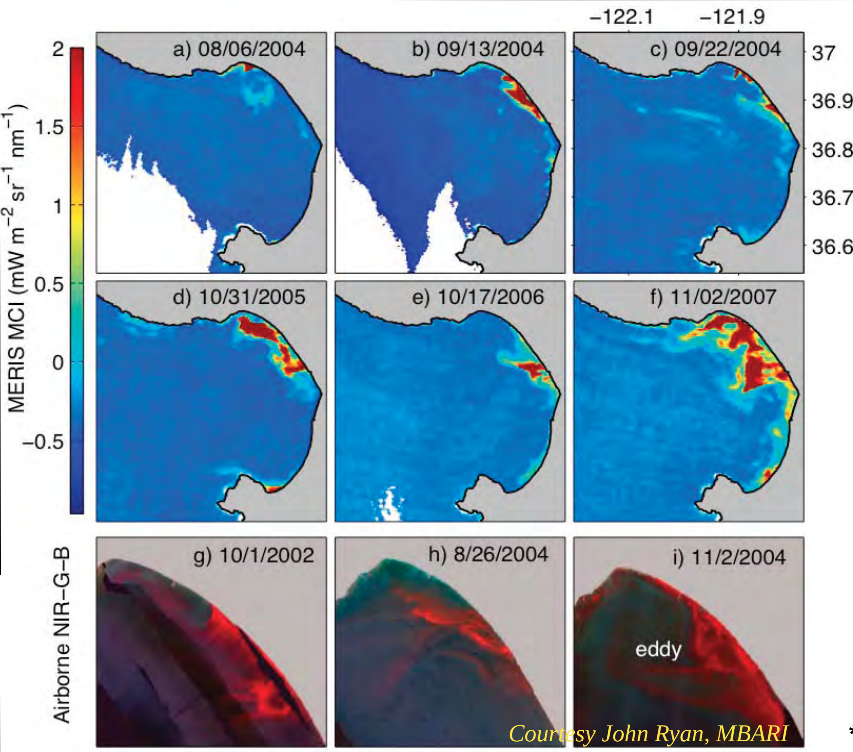




Intermediate Nepheloid Layers (INLs)

- Fluid sheets of *suspended particulates*. Originate from the *sea floor* through diverse fluid dynamics [McPhee-Shaw 2004].
- Large Horizontal Scales (Kms)
- Small Vertical Scales (meters)
- Patchy

Focus of Interest: Event Response for Coast Ocean Processes



Algal Blooms

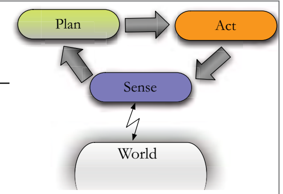
- Regular in episodic appearance in coastal waters everywhere
- Some are harmful; toxins (Demoic acid) generated which cause significant impact to coastal economy and health
  - ✦ Econ. impact ~$75 M ’87-00*
  - ✦ Beach closures
  - ✦ Large mammal deaths
  - ✦ Human health impacts

* D. Anderson, P. Hoagland, Y. Kaoru, and A. White, “*Economic impacts from harmful algal blooms (HABs) in the United States*,” tech. rep., Woods Hole Oceanographic Institution Technical Report: WHOI 2000-11, 2000.

Technological Foci

- Adaptation of a mobile robotic asset in response to dynamic signals in the coastal ocean
- Large scale (interruptible) water-column surveys to target specific features of scientific interest
- To track advected patches of water with specific properties

Technological Foci



- Adaptation of a mobile robotic asset in response to dynamic signals in the coastal ocean
- Large scale (interruptible) water-column surveys to target specific features of scientific interest
- To track advected patches of water with specific properties

Distinction between Autonomy & Automation

- Autonomous Systems:
  - –Sense-Deliberate-Act cycle is intrinsic
  - –Machine-based *decision making* that results in behavior that is emblematic of human behavior
- Automation:
  - –Deliberation is not intrinsic
  - –Machine-based *execution* of activities which alleviates human work

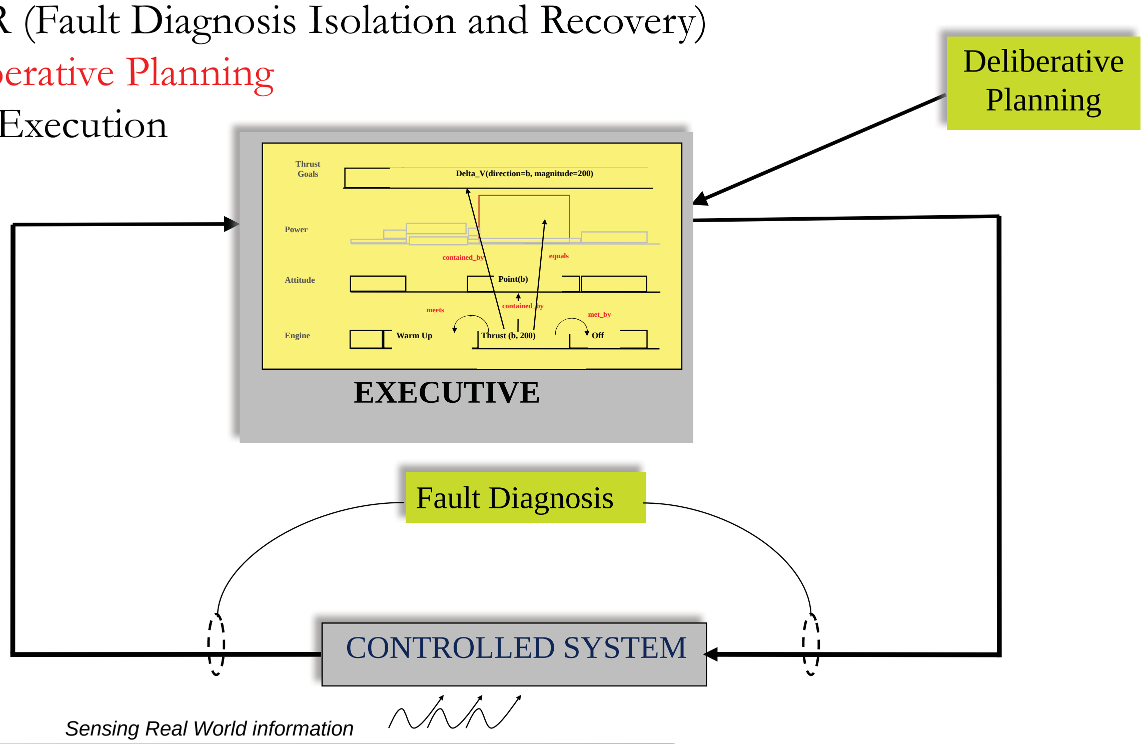
Distinction between Autonomy & Automation

- Autonomous Systems:
  - –Sense-Deliberate-Act cycle is intrinsic
  - –Machine-based *decision making* that results in behavior that is emblematic of human behavior
- Automation:
  - –Deliberation is not intrinsic
  - –Machine-based *execution* of activities which alleviates human work

…..is *not* autonomous

Key Ingredients of an Autonomous System

- FDIR (Fault Diagnosis Isolation and Recovery)
- Deliberative Planning
- Plan Execution



Why is Autonomy important for the Ocean Sciences?

- Communication is not just a bottleneck; its damn difficult in the water-column!
- Powering instruments/platforms is a serious problem
- Costs effectiveness
  - Costs associated with ship based science is increasingly prohibitive
- Given funding profiles, autonomy is a strong leverage to squeeze more science out of existing ocean observing systems
  - Need for looking at the *next* generation of sampling and observation methods
  - Platforms are more robust and increasingly capable
  - Longer durations mission will need:
    - Goal-based commanding
    - Opportunistic re-planning for adaptability
    - Ability to reason about resources
    - Onboard fault diagnosis, isolation and recovery (FDIR)
    - Reduce the cognitive burden of mission operators
    - And to do so efficiently (even at 3am in PIs time-zone)

Why is Autonomy important for the Ocean Sciences?

- Communication is not just a bottleneck; its damn difficult in the water-column!
- Powering instruments/platforms is a serious problem
- Costs effectiveness
  - Costs associated with ship based science is increasingly prohibitive
- Given funding profiles, autonomy is a strong leverage to squeeze more science out of existing ocean observing systems
  - Need for looking at the *next* generation of sampling and observation methods
  - Platforms are more robust and increasingly capable
  - Longer durations mission will need:
    - Goal-based commanding
    - Opportunistic re-planning for adaptability
    - Ability to reason about resources
    - Onboard fault diagnosis, isolation and recovery (FD
    - Reduce the cognitive burden of mission operators
    - And to do so efficiently (even at 3am in PIs time-zo

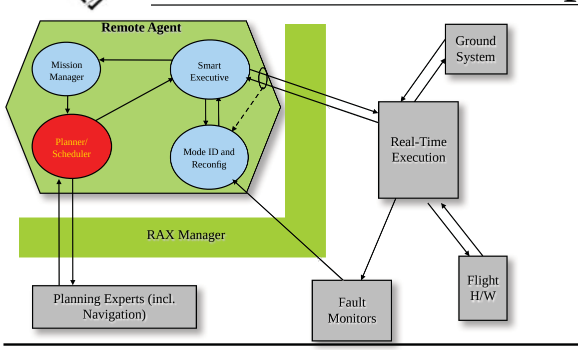
The Sampling Conundrum

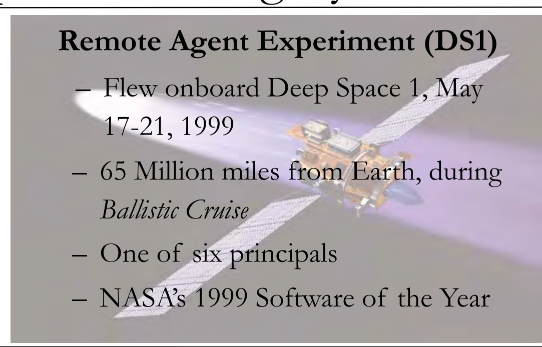
1. Finite Time
2. Finite Energy
3. Finite Sampling Resources
4. Uncertainty of occurrence of phenomenon
5. Uncertainty of location, size, shape and strength of feature signal

Platforms: Ocean going Robots

ROVs | AUVs | Gliders

Intellectual/Operational Legacy of our work

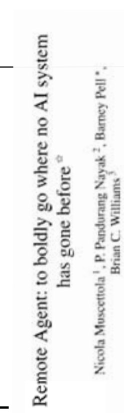


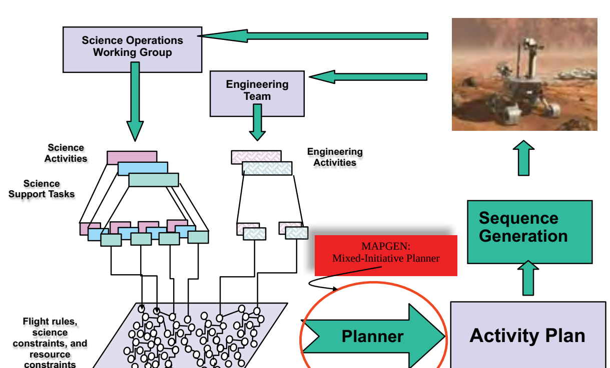


Remote Agent Experiment (DS1)

- Flew onboard Deep Space 1, May 17-21, 1999
- 65 Million miles from Earth, during *Ballistic Cruise*
- One of six principals
- NASA's 1999 Software of the Year

Remote Agent on Deep Space One (DS1)





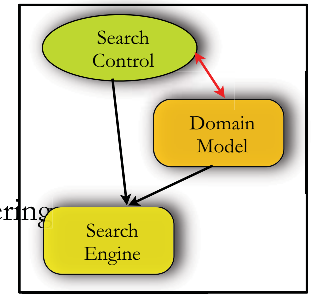
MAPGEN: Mixed-Initiative Activity Planning

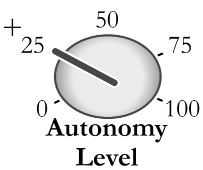
- Jan 14th 2004 - ongoing
- Principal Investigator

Mars Exploration Rovers (MER)

Lessons Learned from Space Missions

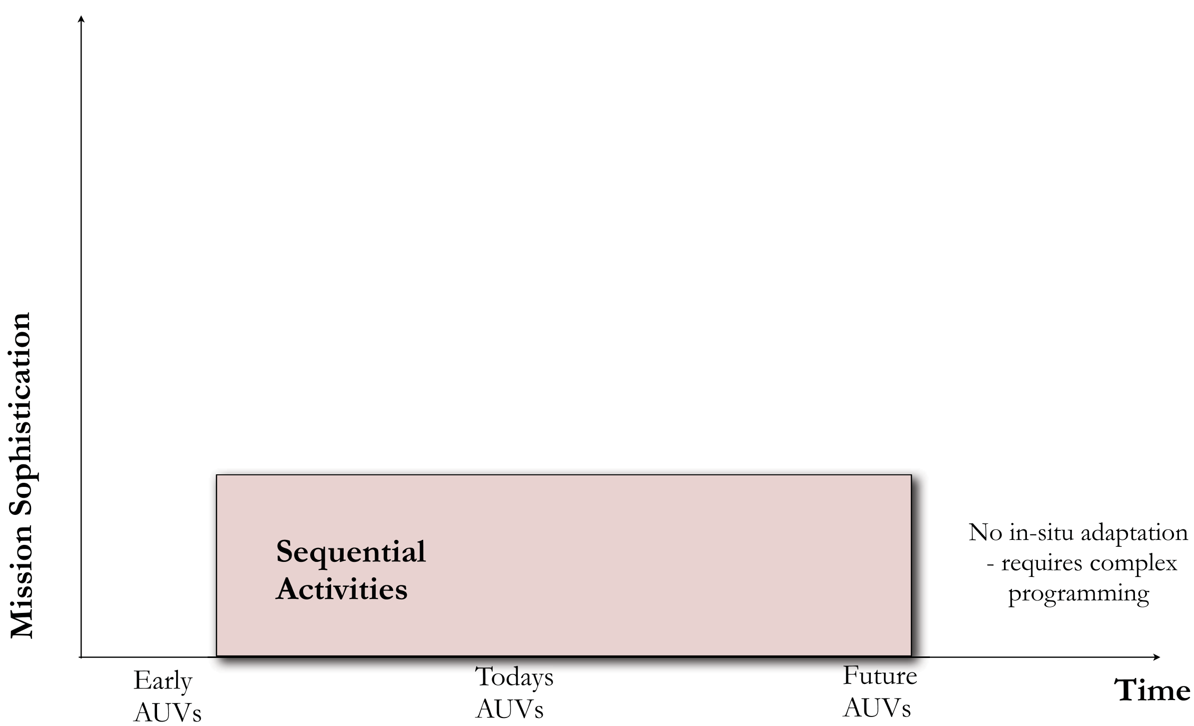
- How (Lessons Learned from DS1 & MER)
  - Customer training and buy-in is not a luxury
  - Requirements change and change often: learn to live with it
  - Test what you fly and fly what you test
  - Spiral mode of development often works well for model-based approaches to s/w engineering
  - All or nothing approach = nothing
    - Incremental use of automated approaches is necessary
    - Solving an existing problem using a dumb but automated method; ++
    - Migrate to more abstract/higher levels of autonomy but slowly.
  - Usability issues should not be ignored
  - Mission-critical software requires good systems engineering
    - Connecting the pieces in the software puzzle
    - Software not developed in isolation to its operating environment
  - Work-practice ethnography is very useful
    - How do people use tools and processes to get the ‘job done’?



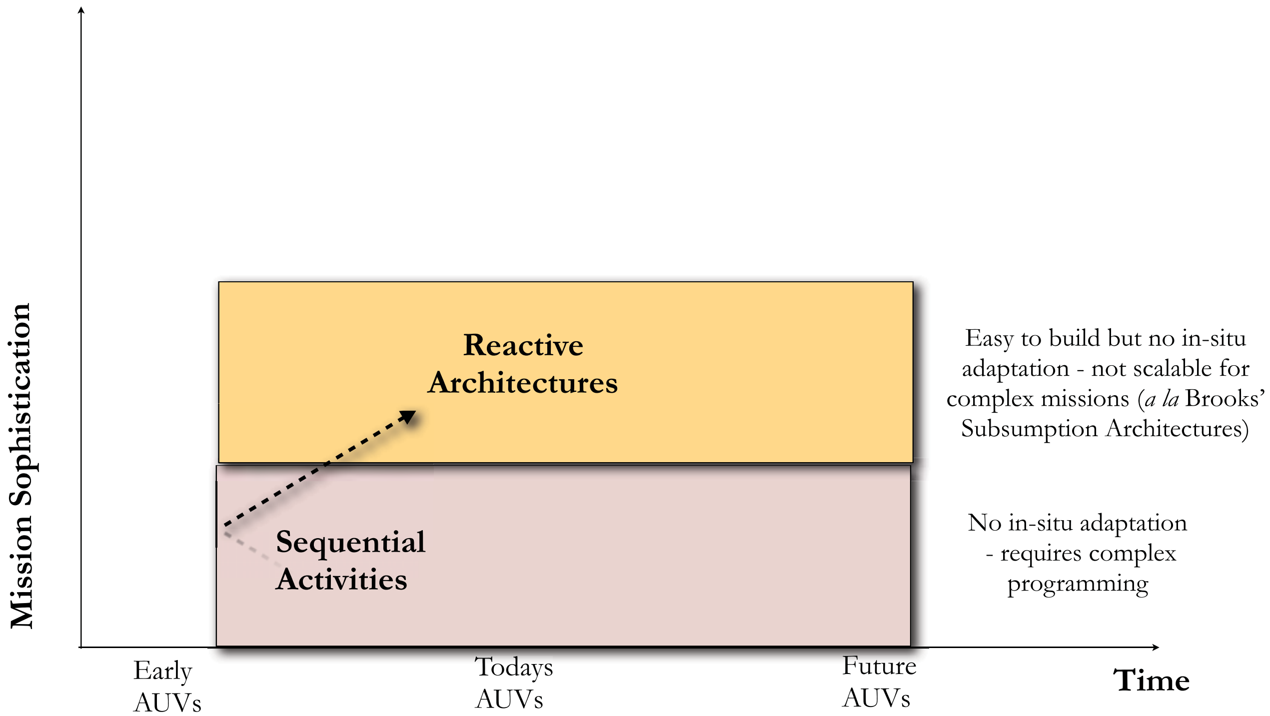


Mars Exploration Rovers/Science Meeting

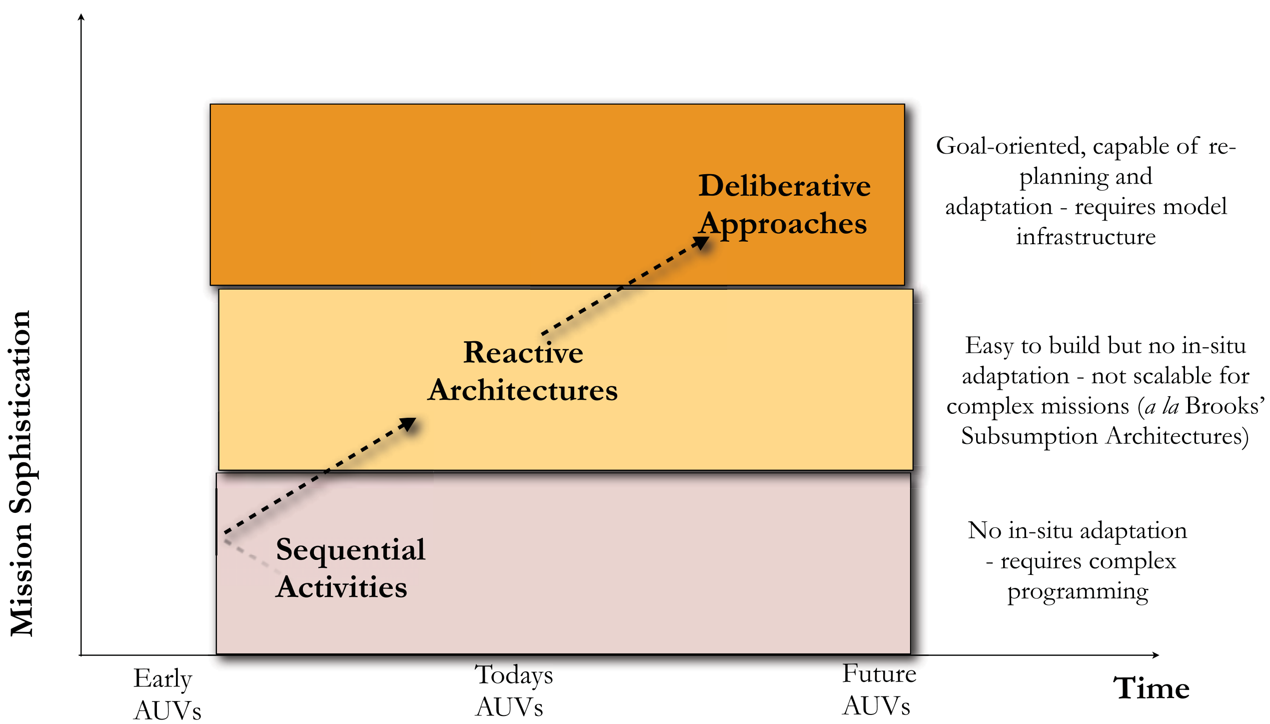
Architectural relationships in the AUV domain



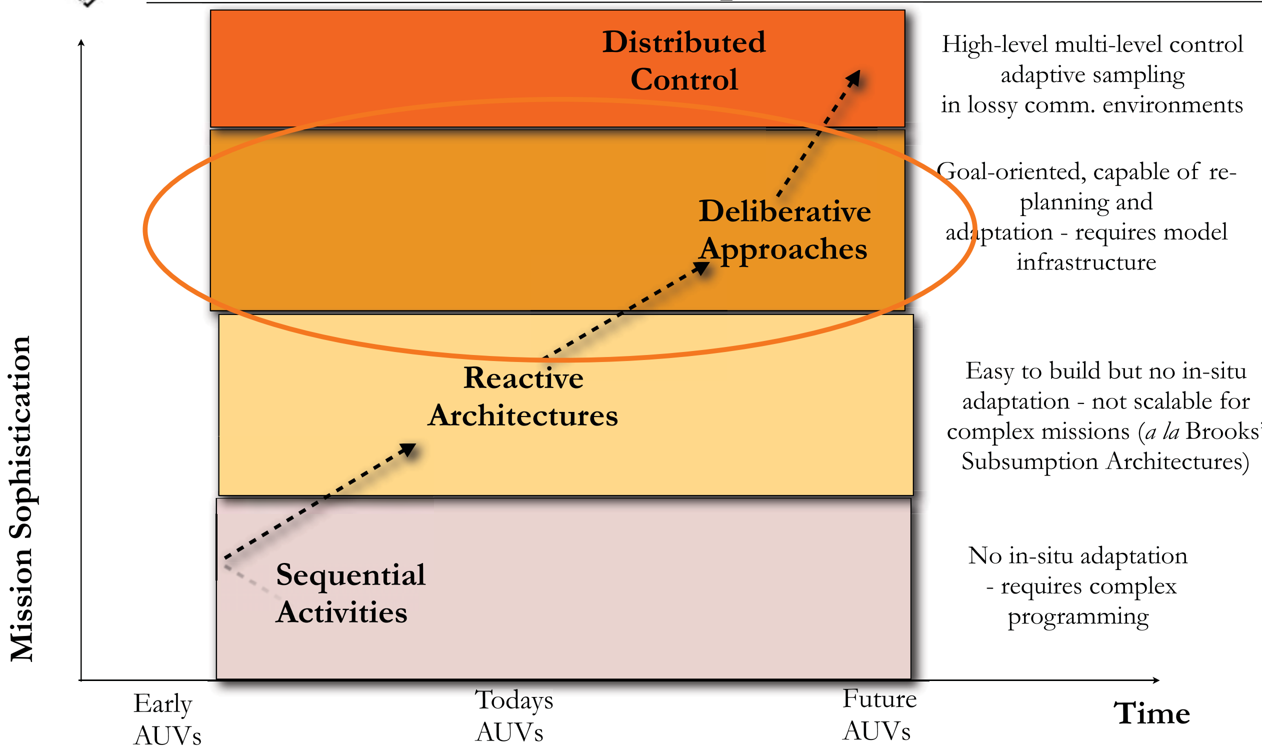
Architectural relationships in the AUV domain



Architectural relationships in the AUV domain

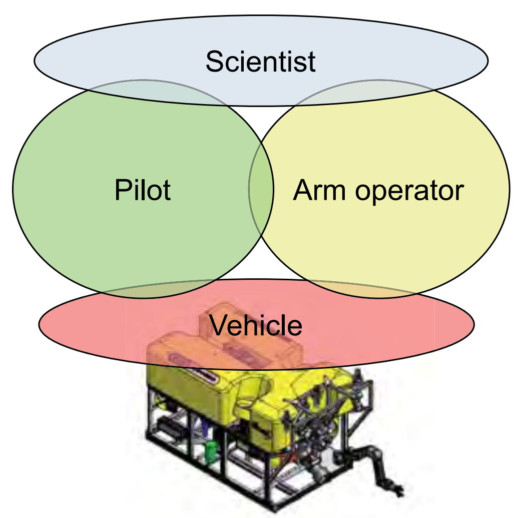


Architectural relationships in the AUV domain



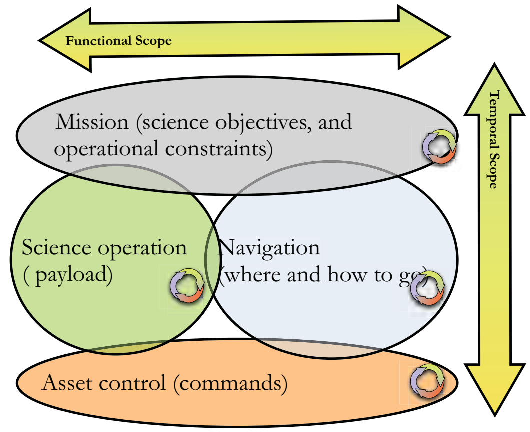
Our Approach for Autonomy

- Abstraction plays a significant role
  - all computation on the robot is not equal
  - all effort to generate a solution is not equal
- All entities can be seen as Sense/Plan/Act (SPA) loops
  - Functional and temporal scope of computation can and should be exploited
  - Partitioning computation should be a necessary and important driver for an agent architecture
- Deliberation and execution are intertwined :
  - decision of one actor can be impacted by observations of another

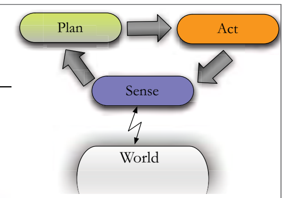


Our Approach for Autonomy

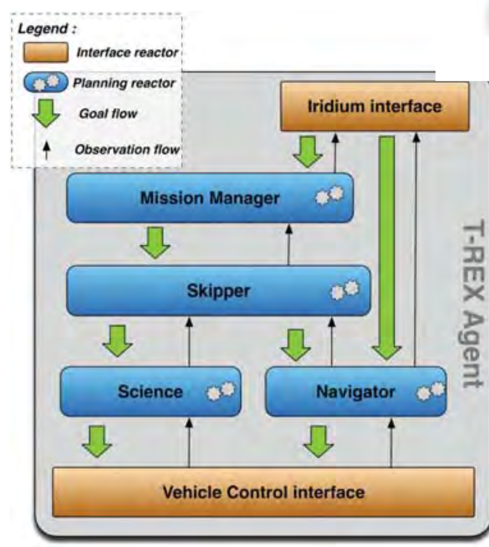
- Abstraction plays a significant role
  - all computation on the robot is not equal
  - all effort to generate a solution is not equal
- All entities can be seen as Sense/Plan/Act (SPA) loops
  - Functional and temporal scope of computation can and should be exploited
  - Partitioning computation should be a necessary and important driver for an agent architecture
- Deliberation and execution are intertwined :
  - decision of one actor can be impacted by observations of another



Our Approach for Autonomy



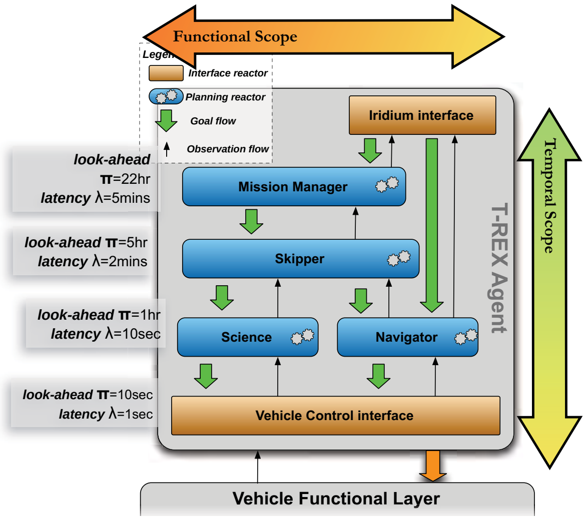
- Abstraction plays a significant role
  - all computation on the robot is not equal
  - all effort to generate a solution is not equal
- All entities can be seen as Sense/Plan/Act (SPA) loops
  - Functional and temporal scope of computation can and should be exploited
  - Partitioning computation should be a necessary and important driver for an agent architecture
- Deliberation and execution are intertwined :
  - decision of one actor can be impacted by observations of another



T-REX: Teleo-Reactive EXecutive

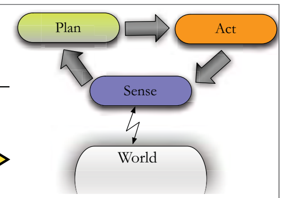
Partitioning Computation

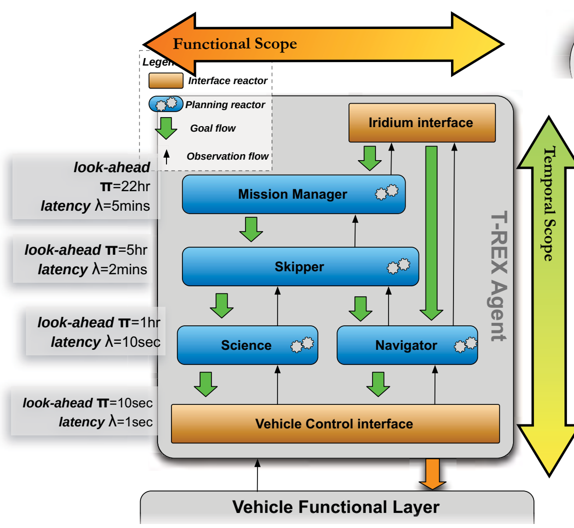
- Functional scope along the lines of *what*
- Temporal scope along the lines of *when*
- What does partitioning buy us?
  - "Divide and Conquer" in problem solving/ Scalability
  - Different search strategies can be encapsulated
  - Incremental model development
  - Allows targeted commanding at any level of abstraction
  - For embedded real-world systems, robustness in failure
  - Identical interfaces making software development easier
  - Reactor contents are agnostic to the T-REX agent

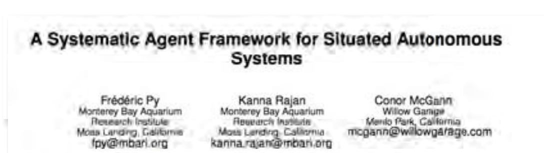


Partitioning Computation

- Functional scope along the lines of *what*
- Temporal scope along the lines of *when*
- What does partitioning buy us?
  - "Divide and Conquer" in problem solving/ Scalability
  - Different search strategies can be encapsulated
  - Incremental model development
  - Allows targeted commanding at any level of abstraction
  - For embedded real-world systems, robustness in failure
  - Identical interfaces making software development easier
  - Reactor contents are agnostic to the T-REX agent



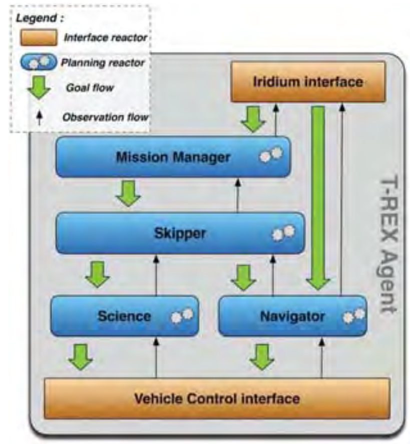



A Systematic Agent Framework for Situated Autonomous Systems

Frédéric Py, Monterey Bay Aquarium Research Institute, Moss Landing, California, fpy@mbari.org
Kanna Rajan, Monterey Bay Aquarium Research Institute, Moss Landing, California, kanna.rajan@mbari.org
Conor McGann, Willow Garage, Menlo Park, California, mcgann@willowgarage.com

Definitions

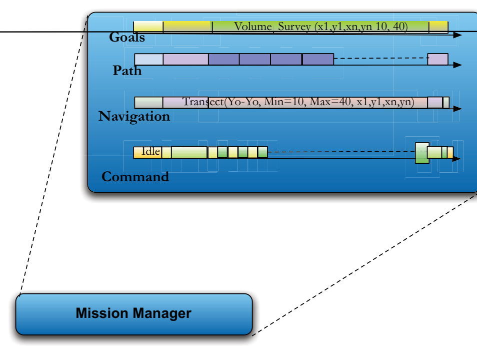
- Each reactor is composed of *timelines*:
  - *Internal* : represent the state of the world as viewed by this reactor
  - *External* : a view of a state variable Internal to another reactor
  - for each *External* timeline there's *one and only one* reactor that defines it as *Internal*
- *timelines* :
  - A sequence of *tokens* that describe the evolution of a state variable
- *tokens :*
  - atomic entity describing a predicate that holds over a temporal scope
  - start, duration and end can be described as intervals (e.g. start=[0, 10])



- *constraints*
  - restrictions over the tokens behavior
  - temporal or parametric

Definitions

- Each reactor is composed of *timelines*:
  - *Internal* : represent the state of the world as viewed by this reactor
  - *External* : a view of a state variable Internal to another reactor
  - for each *External* timeline there's *one and only one* reactor that defines it as *Internal*
- *timelines* :
  - A sequence of *tokens* that describe the evolution of a state variable
- *tokens :*
  - atomic entity describing a predicate that holds over a temporal scope
  - start, duration and end can be described as intervals (e.g. start=[0, 10])

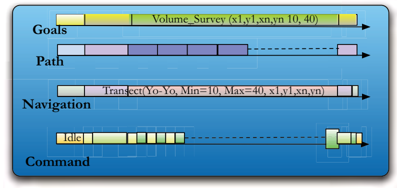


- *constraints*
  - restrictions over the tokens behavior
  - temporal or parametric

Autonomy: Outer to Inner Space *Kanna Rajan,* MBARI *2010*
Friday, December 10, 2010

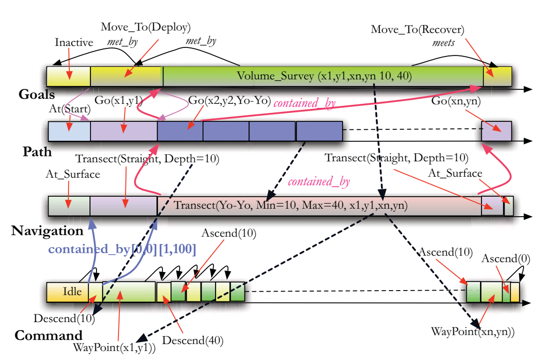
Definitions

- Tokens represent a flexible temporal extant
- Temporal flexibility allows plans to deal with
  - “fail operational” modes
  - uncertainty in plan execution
- use of Allen Algebra for all computation
- Plans are composed of logical assertions of tokens connected by explicit constraints on timelines



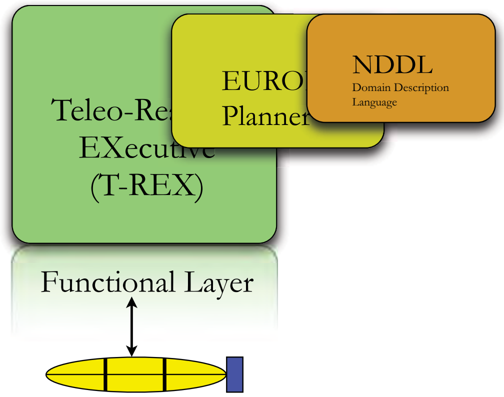
Definitions

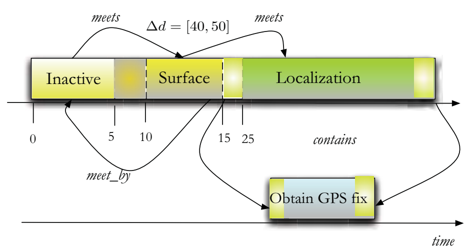
- Tokens represent a flexible temporal extant
- Temporal flexibility allows plans to deal with
  - “fail operational” modes
  - uncertainty in plan execution
- use of Allen Algebra for all computation
- Plans are composed of logical assertions of tokens connected by explicit constraints on timelines



Definitions

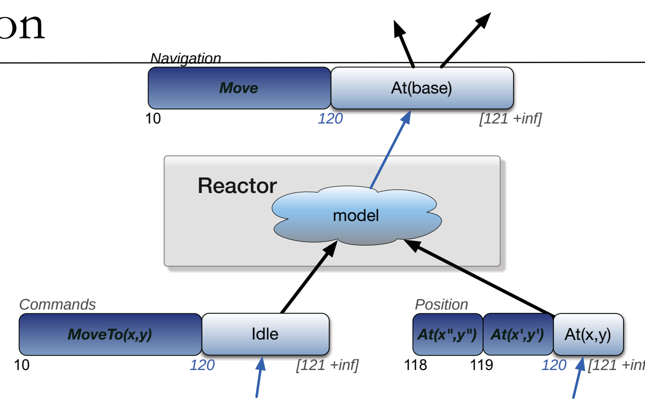
- Tokens represent a flexible temporal extant
- Temporal flexibility allows plans to deal with
  - "fail operational" modes
  - uncertainty in plan execution
- use of Allen Algebra for all computation
- Plans are composed of logical assertions of tokens connected by explicit constraints on timelines



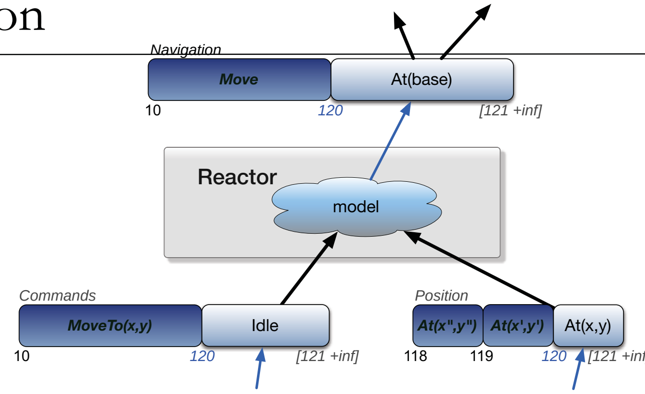


Sensing : Synchronization

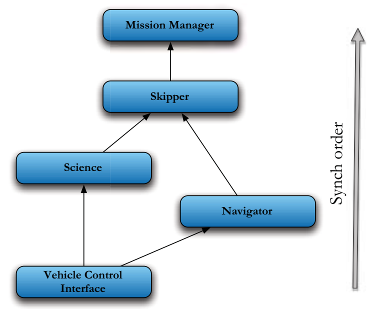
- Synchronization is the operation during which a reactor identifies its current state
  - merging observations with expectations
  - computes the current value of its *Internal timelines*
- The *Internal* state depends on *External* timelines
  - Cannot synchronize unless the reactors it depends on are synchronized



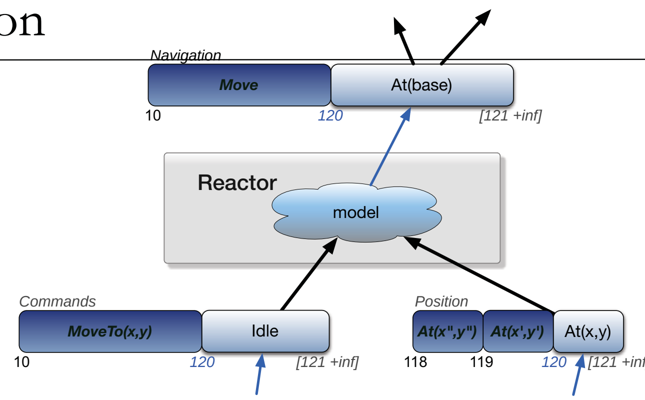
Sensing : Synchronization



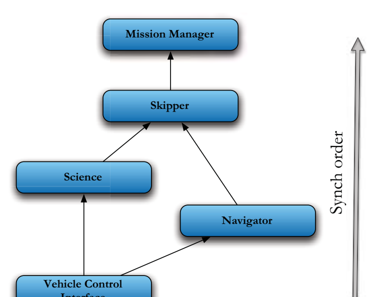
- Synchronization is the operation during which a reactor identifies its current state
  - merging observations with expectations
  - computes the current value of its *Internal timelines*
- The *Internal* state depends on *External* timelines
  - Cannot synchronize unless the reactors it depends on are synchronized



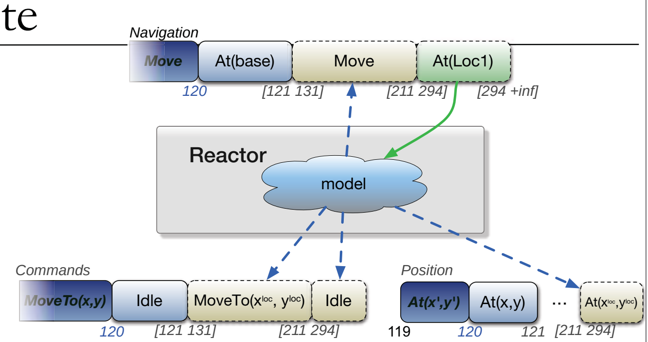
Sensing : Synchronization



- Synchronization is the operation during which a reactor identifies its current state
  - merging observations with expectations
  - computes the current value of its *Internal timelines*
- The *Internal* state depends on *External* timelines
  - Cannot synchronize unless the reactors it depends on are synchronized
- Role of the TREX agent:
  - Order reactor synchronization based on their dependencies
  - Propagate *Internal* state updates to the corresponding *External* timelines

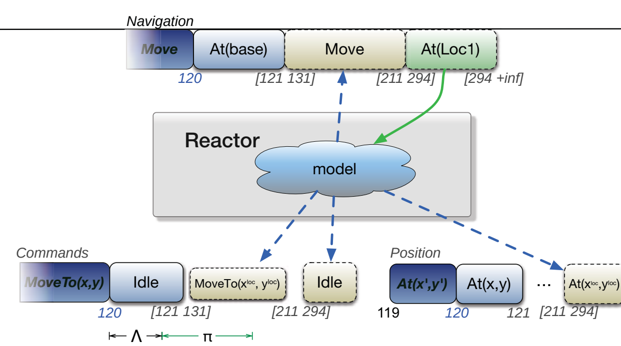


Plan/Deliberate



- Deliberation is purely internal to the reactor
  - find how to alter *External* states in order to be in a desired *Internal* state
- 2 possible triggers for deliberation :
  - a new goal on its *Internal* state
  - *External* observations contradict reactor's plan leading to plan repair/failure
- Each reactor defines two important parameters :
  - latency λ : maximum time required for producing a plan
  - look-ahead π : how far ahead the reactor needs to look for deliberation

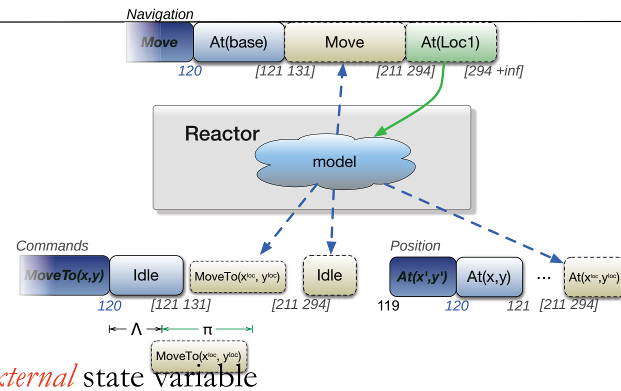
Act : Dispatching



- In order to execute its plan the reactor should be able to request *External* timelines to change according to its plan
- This dispatching can be done when a planned state overlaps the planning window of the owner of this *External* state variable
- *planning window* = $[\tau+\Lambda_{exec}, \tau+\Lambda_{exec}+\pi]$
  - Λ_{exec} is the execution latency of a reactor including :
    - reactor's deliberation latency (λ)
    - and the maximum Λ_{exec} of its *External* states
- A newly dispatched token becomes a *goal* of the owner of this *External* state (i.e. the one declaring it as *Internal*)

Act : Dispatching

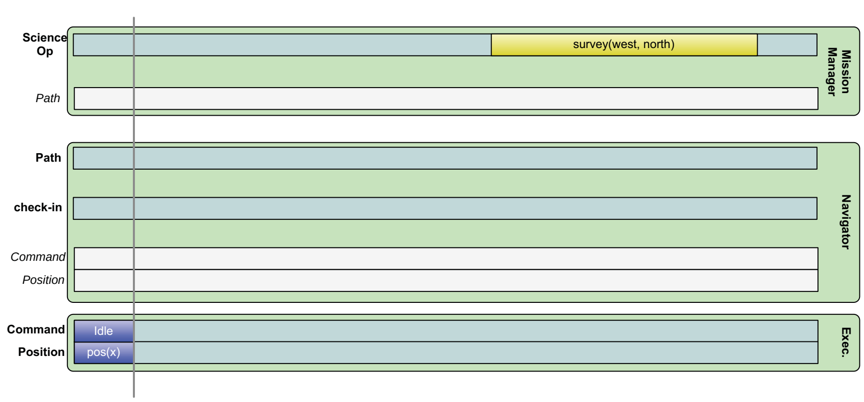
- In order to execute its plan the reactor should be able to request *External* timelines to change according to its plan



- This dispatching can be done when a planned state overlaps the planning window of the owner of this *External* state variable
- *planning window* = $[\tau+\Lambda_{exec}, \tau+\Lambda_{exec}+\pi]$
  - Λ_{exec} is the execution latency of a reactor including :
    - reactor's deliberation latency (λ)
    - and the maximum Λ_{exec} of its *External* states
- A newly dispatched token becomes a *goal* of the owner of this *External* state (i.e. the one declaring it as *Internal*)

Illustration

- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



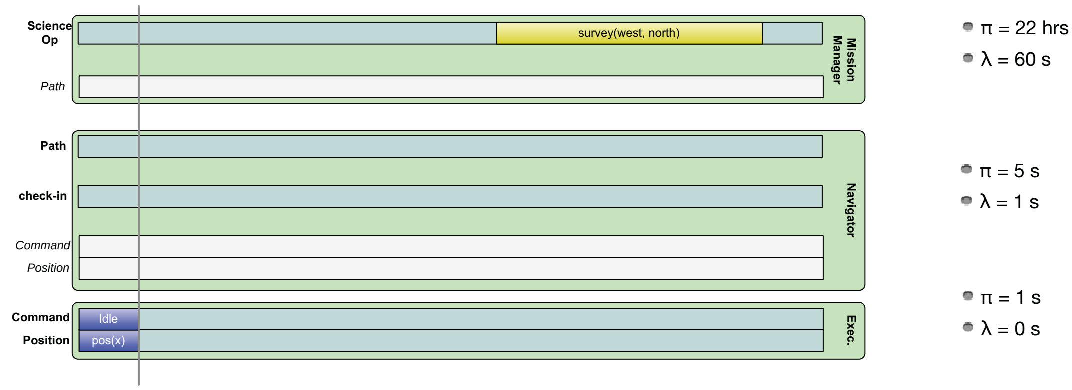
- π = 22 hrs
- λ = 60 s

- π = 5 s
- λ = 1 s

- π = 1 s
- λ = 0 s

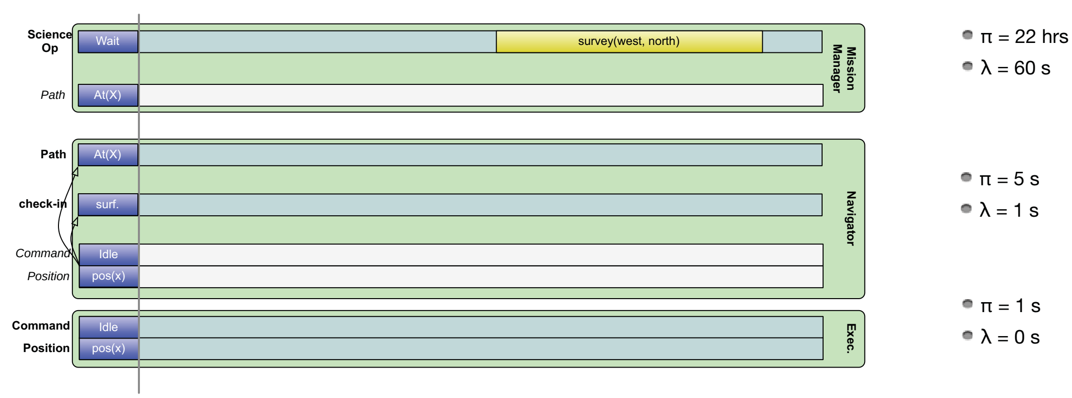
Illustration

- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



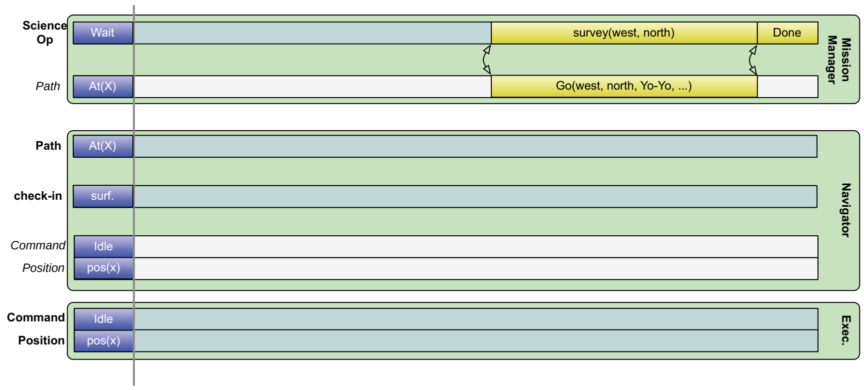
Illustration

- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



Illustration

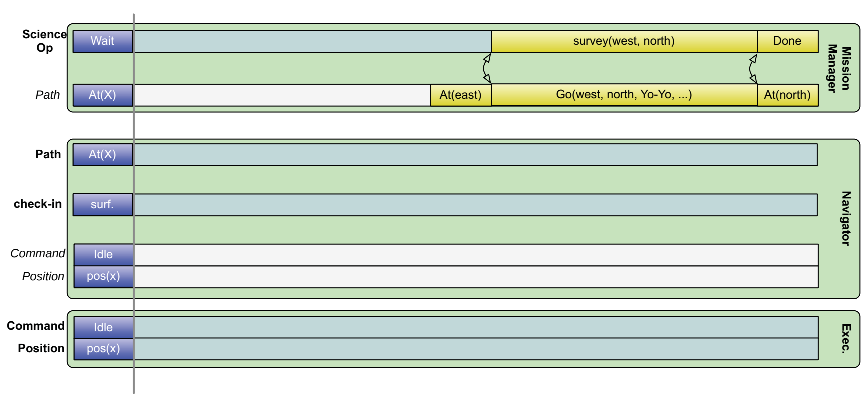
- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



- π = 22 hrs
- λ = 60 s
- π = 5 s
- λ = 1 s
- π = 1 s
- λ = 0 s

Illustration

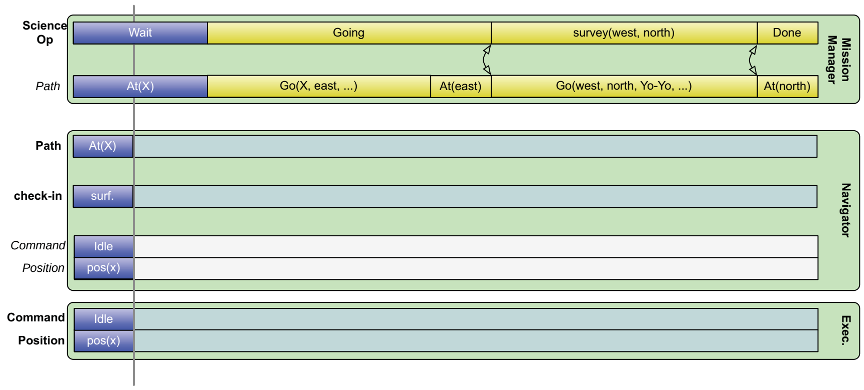
- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



- π = 22 hrs
- λ = 60 s
- π = 5 s
- λ = 1 s
- π = 1 s
- λ = 0 s

Illustration

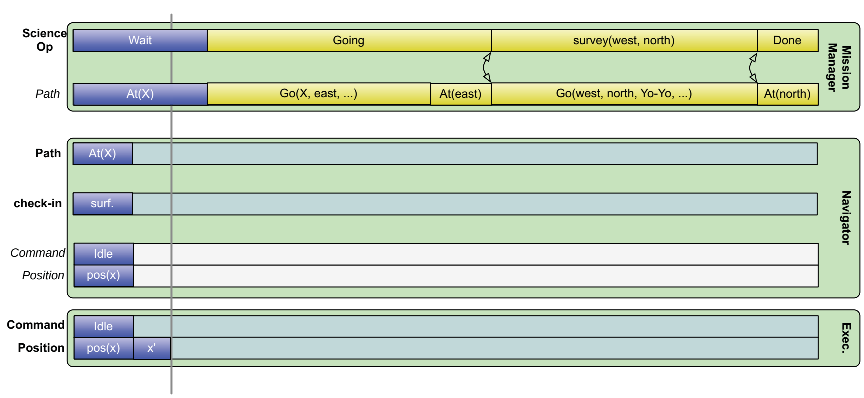
- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



- π = 22 hrs
- λ = 60 s
- π = 5 s
- λ = 1 s
- π = 1 s
- λ = 0 s

Illustration

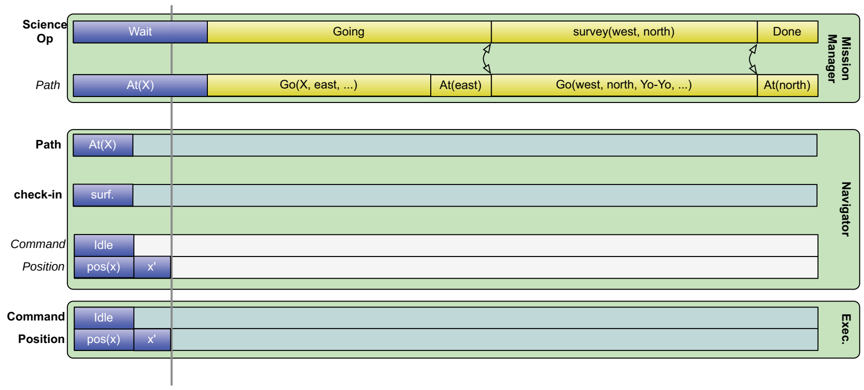
- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



- π = 22 hrs
- λ = 60 s
- π = 5 s
- λ = 1 s
- π = 1 s
- λ = 0 s

Illustration

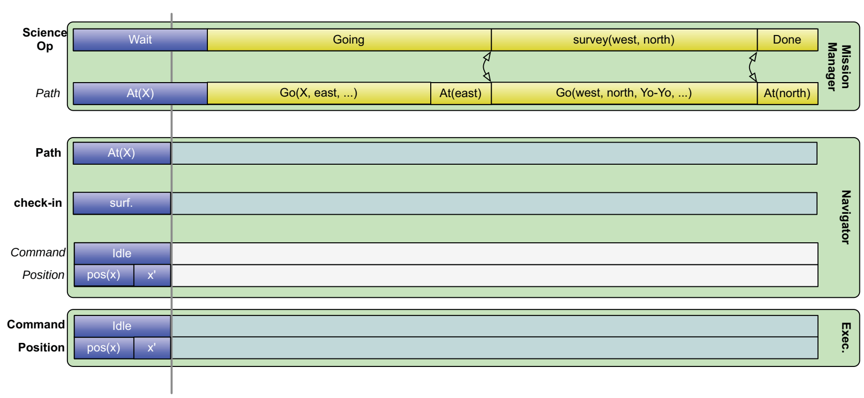
- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



- π = 22 hrs
- λ = 60 s
- π = 5 s
- λ = 1 s
- π = 1 s
- λ = 0 s

Illustration

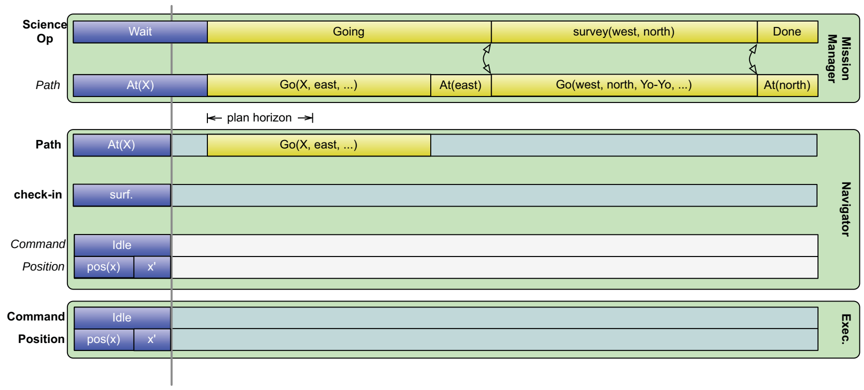
- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



- π = 22 hrs
- λ = 60 s
- π = 5 s
- λ = 1 s
- π = 1 s
- λ = 0 s

Illustration

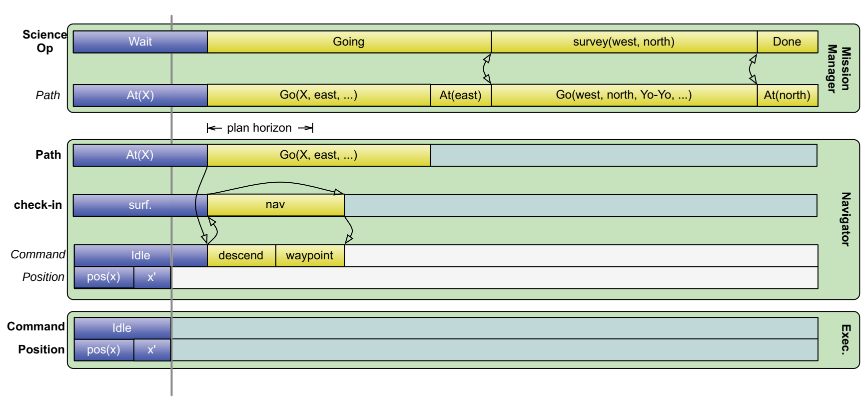
- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



- π = 22 hrs
- λ = 60 s
- π = 5 s
- λ = 1 s
- π = 1 s
- λ = 0 s

Illustration

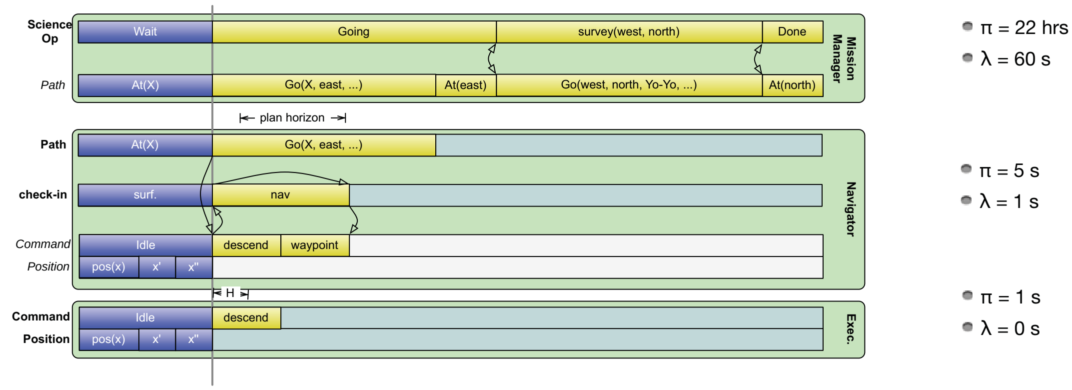
- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



- π = 22 hrs
- λ = 60 s
- π = 5 s
- λ = 1 s
- π = 1 s
- λ = 0 s

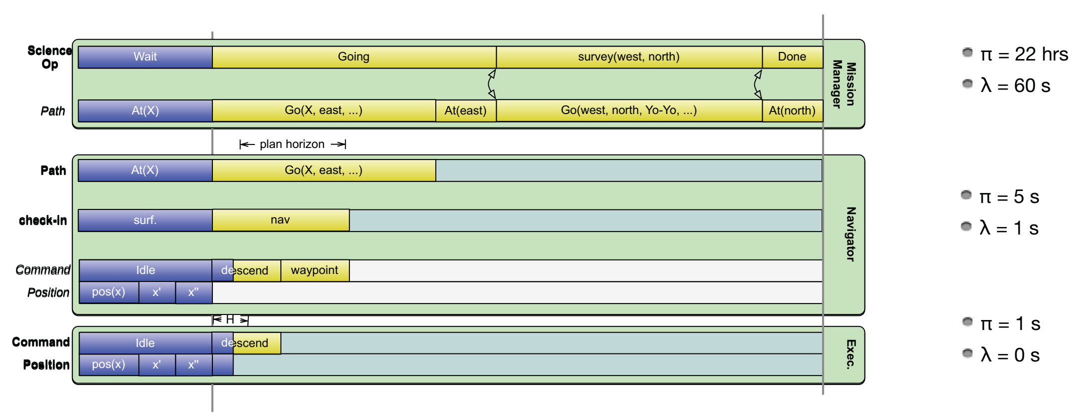
Illustration

- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



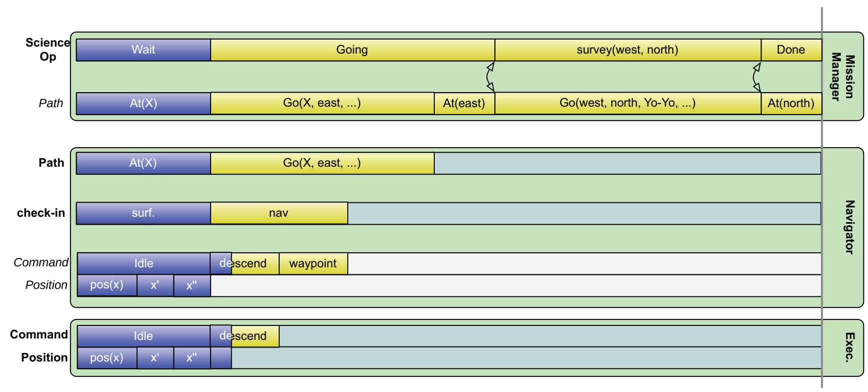
Illustration

- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



Illustration

- 3 reactors
  - *Mission Manager* : select and order scientific goals to do in the mission
  - *Navigator* : Waypoint based navigation control including operational constraints (surface every ~30mins for localization, ...)
  - *Executive* : dispatch commands and collect data from the vehicle



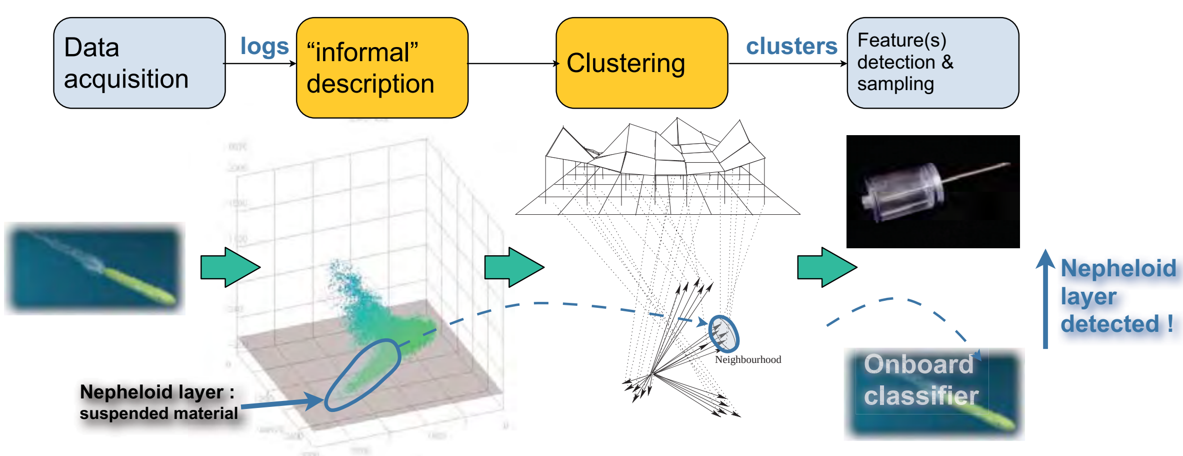
- π = 22 hrs
- λ = 60 s

- π = 5 s
- λ = 1 s

- π = 1 s
- λ = 0 s

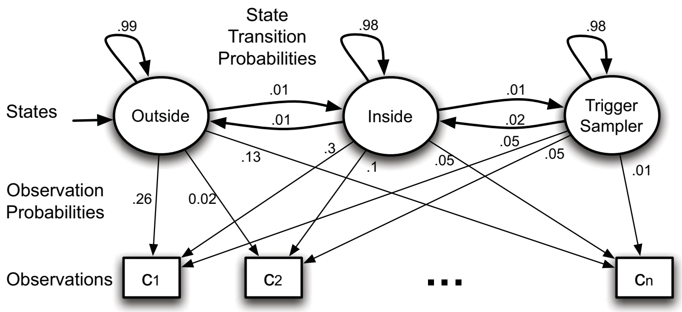
Integrating HMM's with Planning

- Need a generic way to identify features from sensor data in real-time
  - Idea : learn a model from previous missions
  - Technique : Use clustering to extract information from raw-data



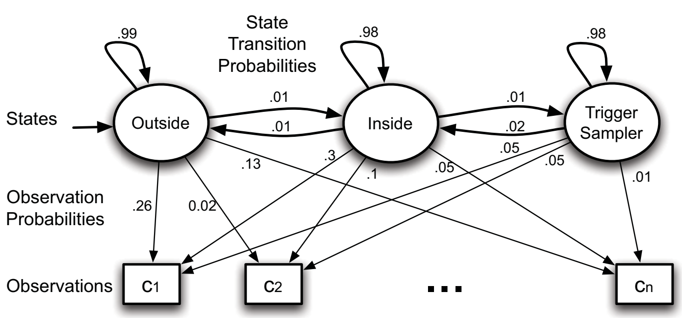
Integrating HMM's with Planning: Next Steps

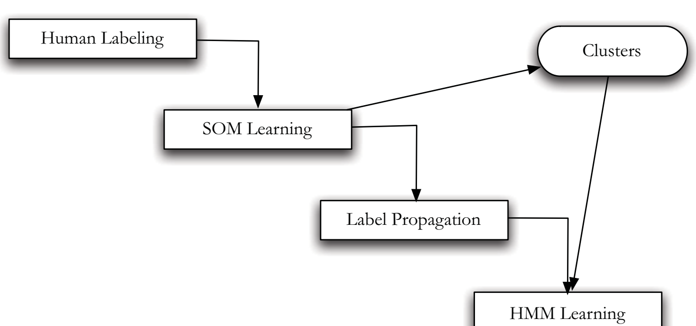
Objective: To provide the context of the *sequence* of observations to enable state estimation

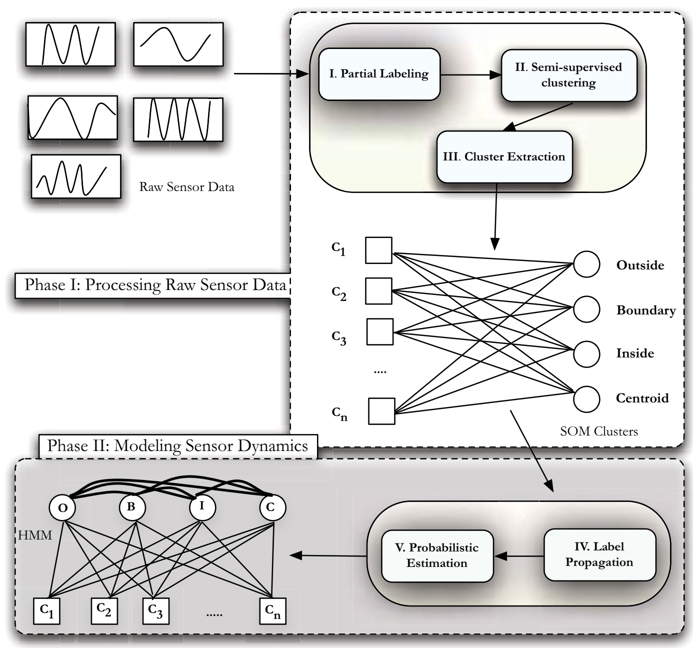


Integrating HMM's with Planning: Next Steps

Objective: To provide the context of the *sequence* of observations to enable state estimation

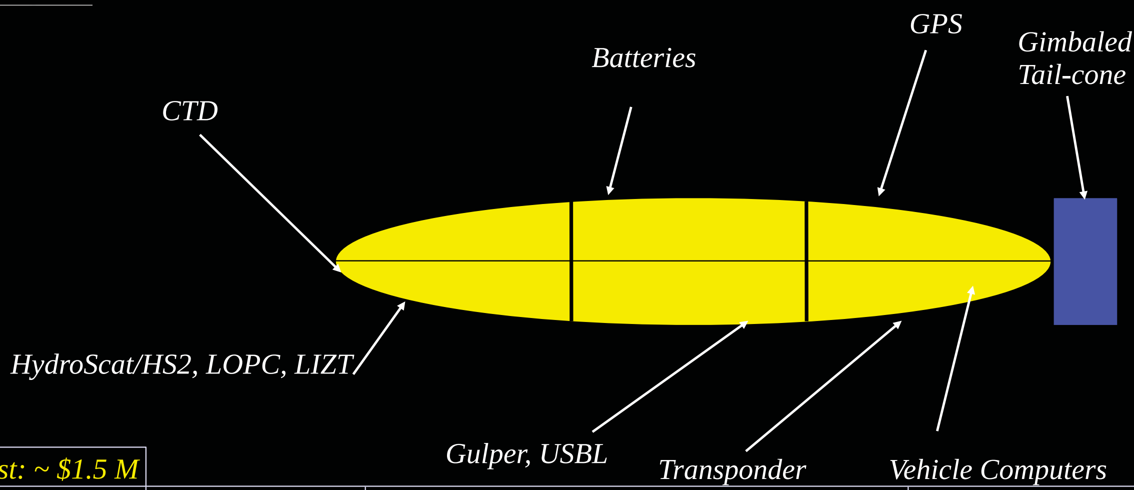






Machine Learning for In-situ Sampling of Ocean Features
F. Py, S. Celorrio, K. Rajan *in review*

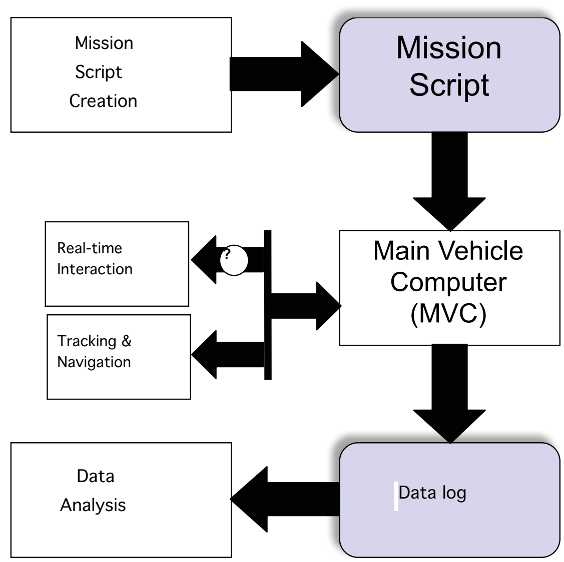
MBARI's CTD* AUV



Cost: ~ $1.5 M

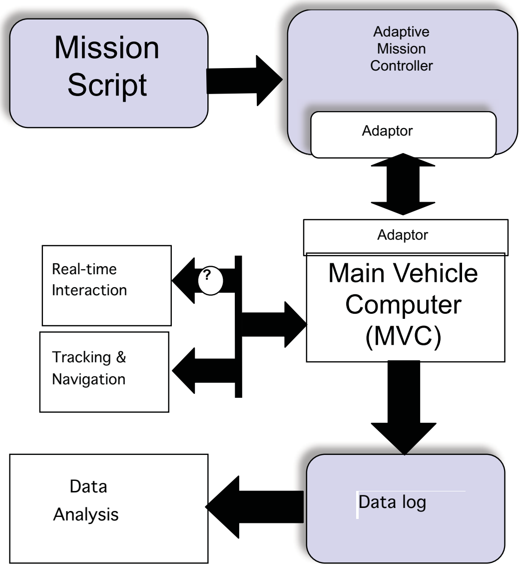
Speed 4knots	*Length: 4.3 m (typical), Diameter: 0.53m*	*Endurance ~22hrs*
Depth rating 4500m/typical 1000m	*Missions: Upper water-column, time-series, engineering testing*	*Frequency of use: 4 days/week*
CPU: 1 300 Mhz PC-104 Functional Layer/QNX, 367 Mhz 1 EPIC EPX-GX500/Fedora RH7	*Launch/Recovery: R/V Zephyr*	* *Conductivity, Temperature, Depth*

T-REX's Embodiment



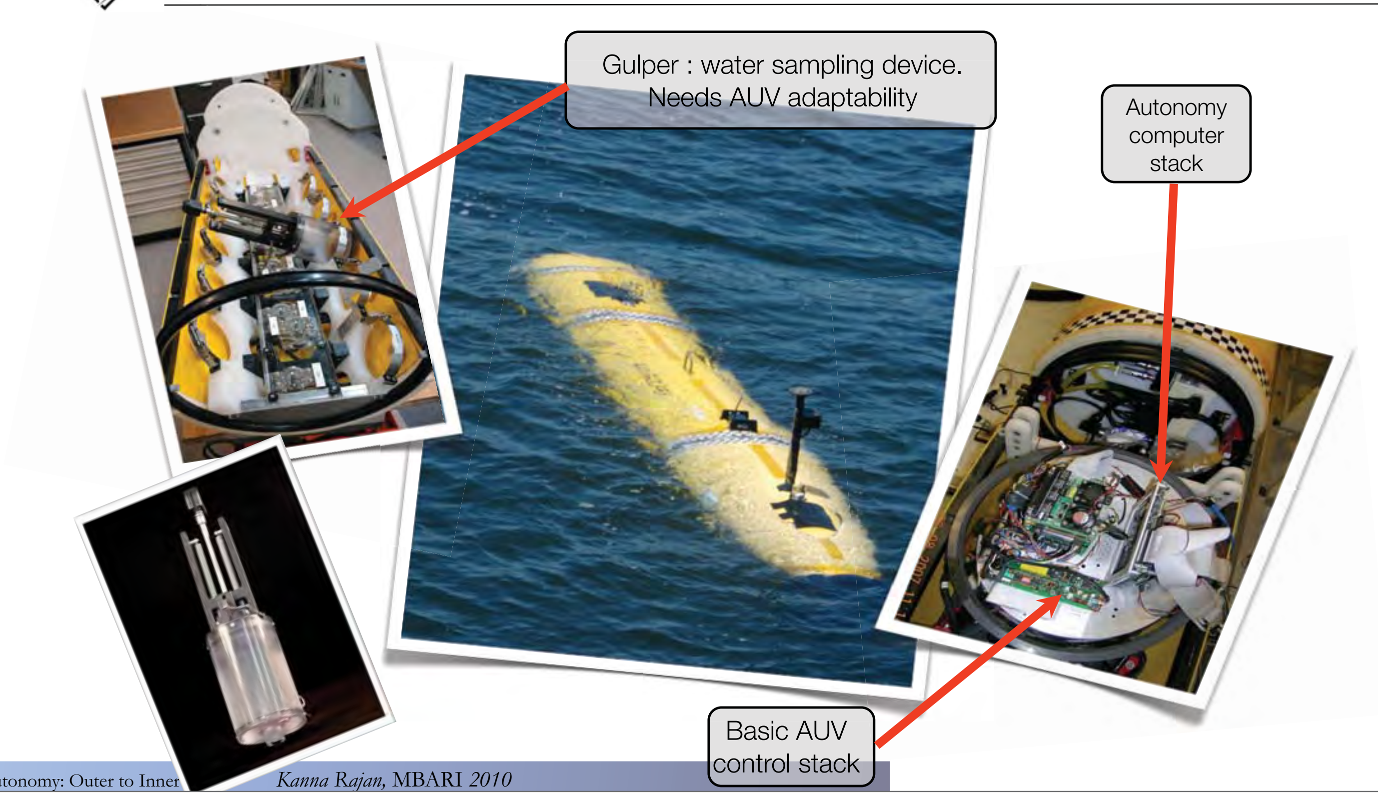
What was done before

T-REX's Embodiment



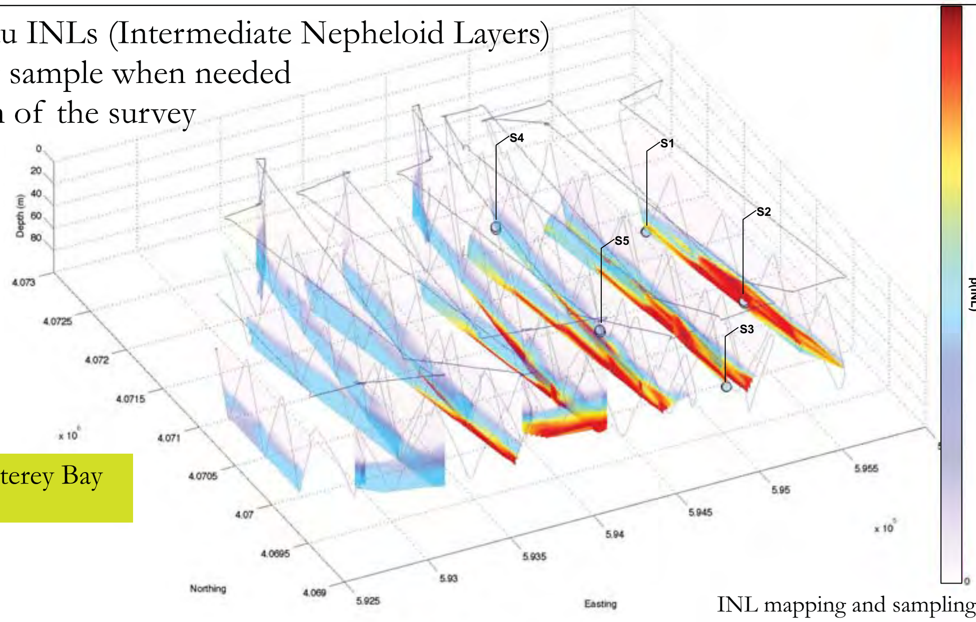
What we can do now

T-REX's Embodiment



Results:Volume Surveys

- Ability to detect in-situ INLs (Intermediate Nepheloid Layers)
- Reactively takes water sample when needed
- Change the resolution of the survey



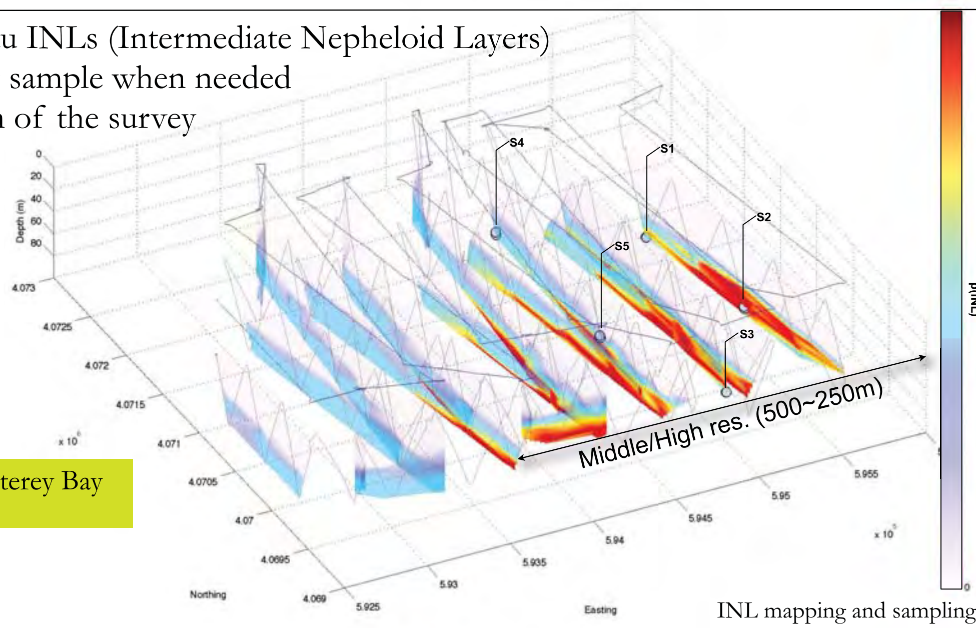
Location: Off M0 Monterey Bay
Nov 2009

INL mapping and sampling survey around M0

- Mission duration up to 6 hours
- Average CPU load ~20% including execution control, planning and state estimation

Results:Volume Surveys

- Ability to detect in-situ INLs (Intermediate Nepheloid Layers)
- Reactively takes water sample when needed
- Change the resolution of the survey



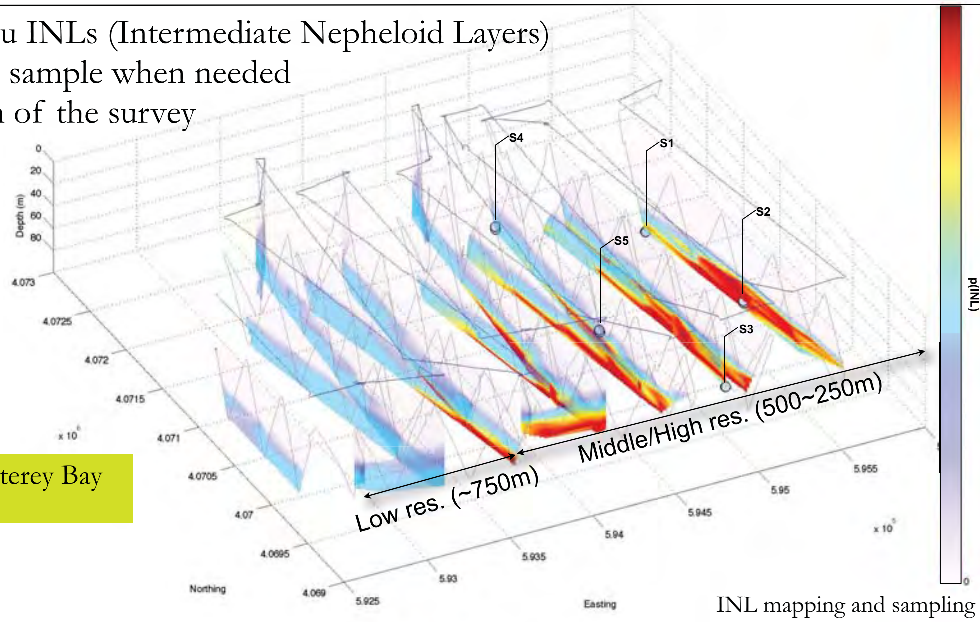
Location: Off M0 Monterey Bay
Nov 2009

INL mapping and sampling survey around M0

- Mission duration up to 6 hours
- Average CPU load ~20% including execution control, planning and state estimation

Results:Volume Surveys

- Ability to detect in-situ INLs (Intermediate Nepheloid Layers)
- Reactively takes water sample when needed
- Change the resolution of the survey



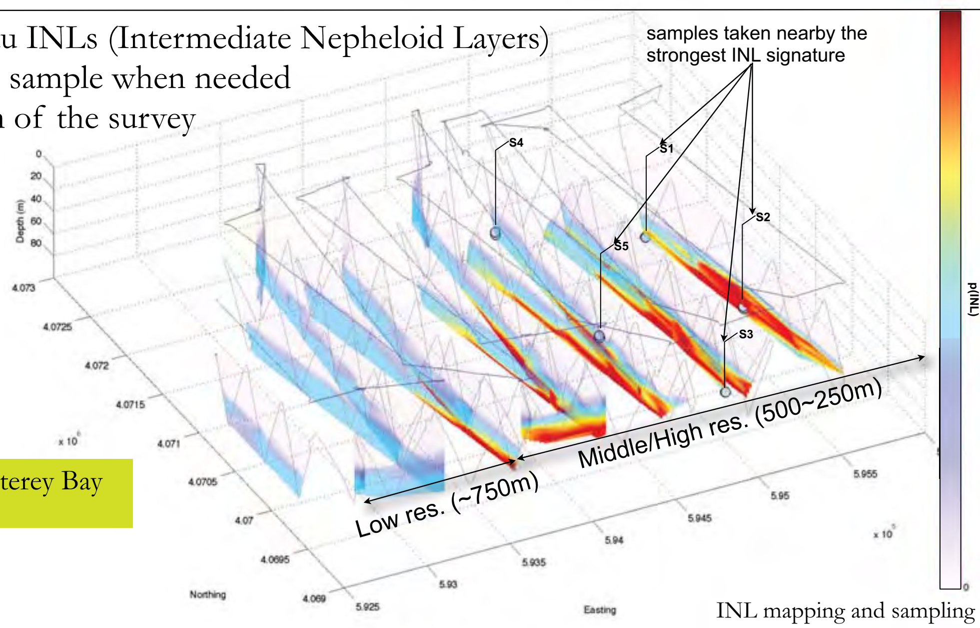
Location: Off M0 Monterey Bay
Nov 2009

INL mapping and sampling survey around M0

- Mission duration up to 6 hours
- Average CPU load ~20% including execution control, planning and state estimation

Results:Volume Surveys

- Ability to detect in-situ INLs (Intermediate Nepheloid Layers)
- Reactively takes water sample when needed
- Change the resolution of the survey



Location: Off M0 Monterey Bay
Nov 2009

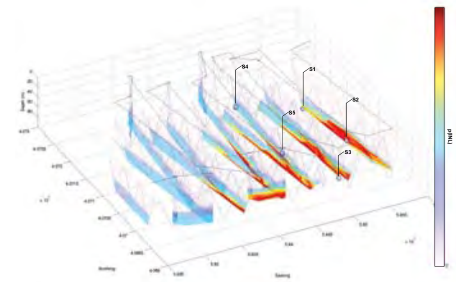
INL mapping and sampling survey around M0

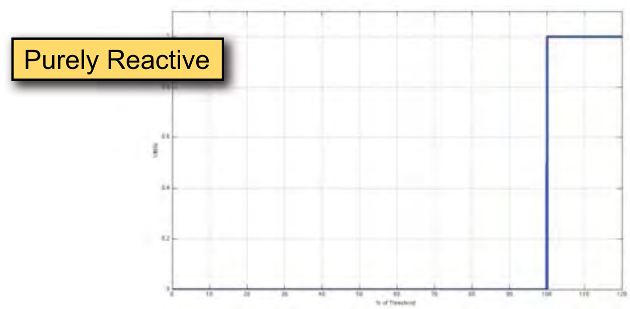
- Mission duration up to 6 hours
- Average CPU load ~20% including execution control, planning and state estimation

Autonomy: Outer to Inner Space *Kanna Rajan,* MBARI *2010*
Friday, December 10, 2010

Adaptive Sampling: The Role of Sample Utility

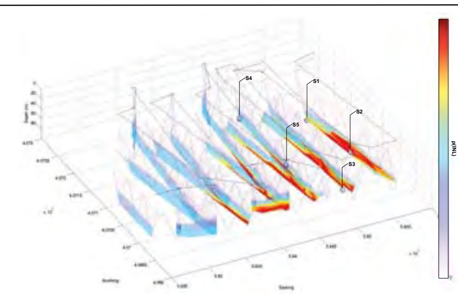
- Problem: To determine when and where samples are to be acquired for *maximum information gain*, while respecting spatial and temporal sampling constraints.
- Proposed solution: Use utility functions as a means to inform plan-time decisions
  - Weakly Informed: tracking history - past samples
  - Mission Aware: plan analysis - time/traverses remaining
  - Feature Aware: a priori knowledge of feature

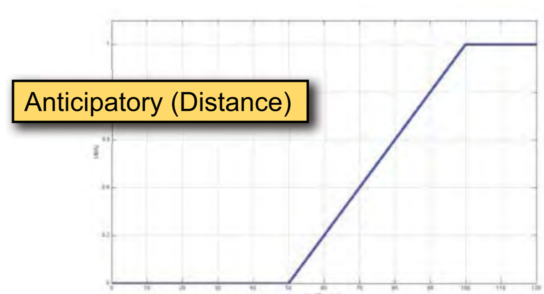




Adaptive Sampling: The Role of Sample Utility

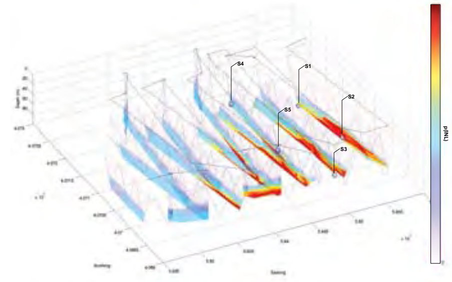
- Problem: To determine when and where samples are to be acquired for *maximum information gain*, while respecting spatial and temporal sampling constraints.
- Proposed solution: Use utility functions as a means to inform plan-time decisions
  - Weakly Informed: tracking history - past samples
  - Mission Aware: plan analysis - time/traverses remaining
  - Feature Aware: a priori knowledge of feature

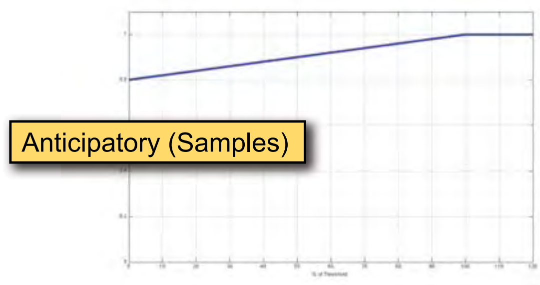




Adaptive Sampling: The Role of Sample Utility

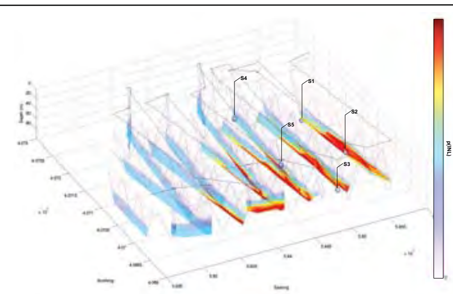
- Problem: To determine when and where samples are to be acquired for *maximum information gain*, while respecting spatial and temporal sampling constraints.
- Proposed solution: Use utility functions as a means to inform plan-time decisions
  - Weakly Informed: tracking history - past samples
  - Mission Aware: plan analysis - time/traverses remaining
  - Feature Aware: a priori knowledge of feature



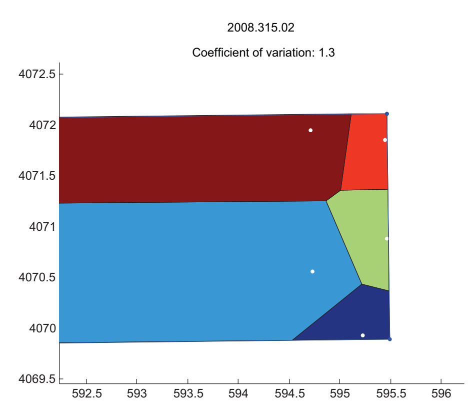


Adaptive Sampling: The Role of Sample Utility

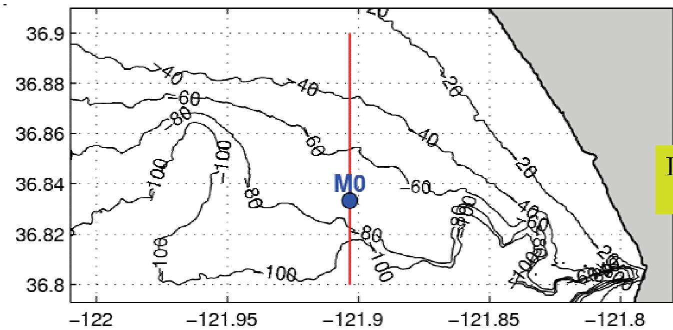
- Problem: To determine when and where samples are to be acquired for *maximum information gain*, while respecting spatial and temporal sampling constraints.
- Proposed solution: Use utility functions as a means to inform plan-time decisions
  - Weakly Informed: tracking history - past samples
  - Mission Aware: plan analysis - time/traverses remaining
  - Feature Aware: a priori knowledge of feature



- Given certain space and a set K of points in this space, the Voronoi region for any $k_i \in K$ contains all the points of the space that are closer to ki than to any other kj.
- Good indicator of spatial distribution of samples
- But spatial distribution is not all that matters:
  - large areas could correspond to small probability areas...
- Solution: integral of the probability of all the points contained in a certain Voronoi region

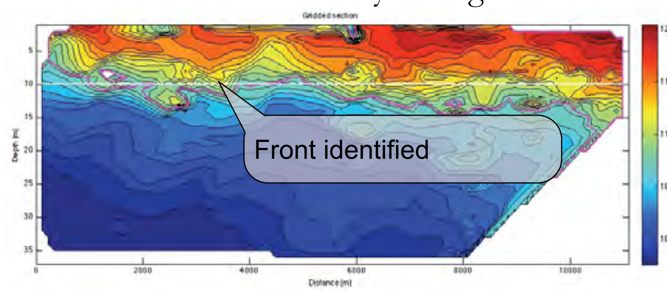


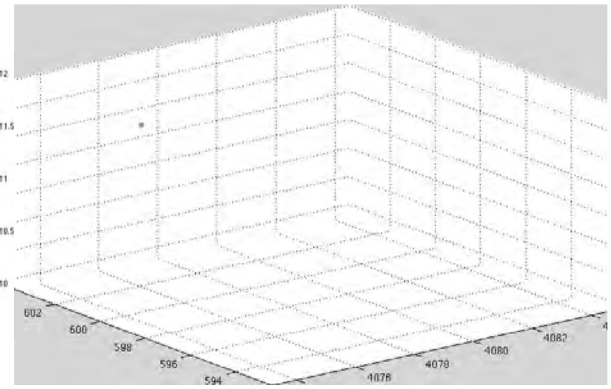
Results: Following Fronts



Location: Off M0 Monterey Bay
July 2009

Data sent to shore continuously during transect





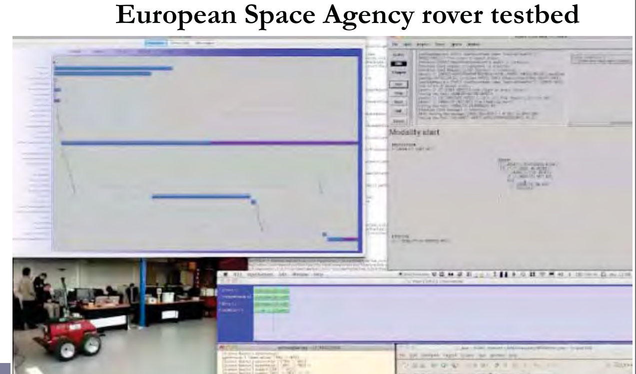
Results: Other TREX Instantiations

- T-REX is a general purpose Open Source framework (in Google Code)
  - Anything that can be described as Sense/Plan/Act can be integrated as a reactor
- T-REX is being used to coordinate multiple planners for advanced service robot control (http://www.willowgarage.com):

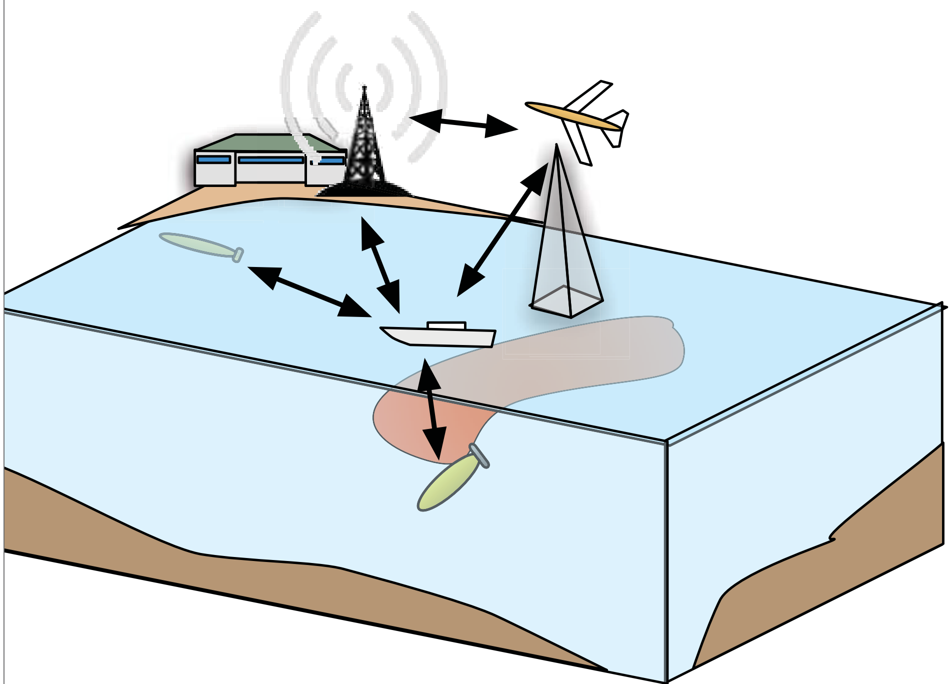
PR2 control

- T-REX will be the core controller for ESA rover testbed:
  - IP-CNR (Italy): APSI Planner
  - LAAS (France) : GenoM functionnal layer
  - Verimag (France) : BIP compositional Verification

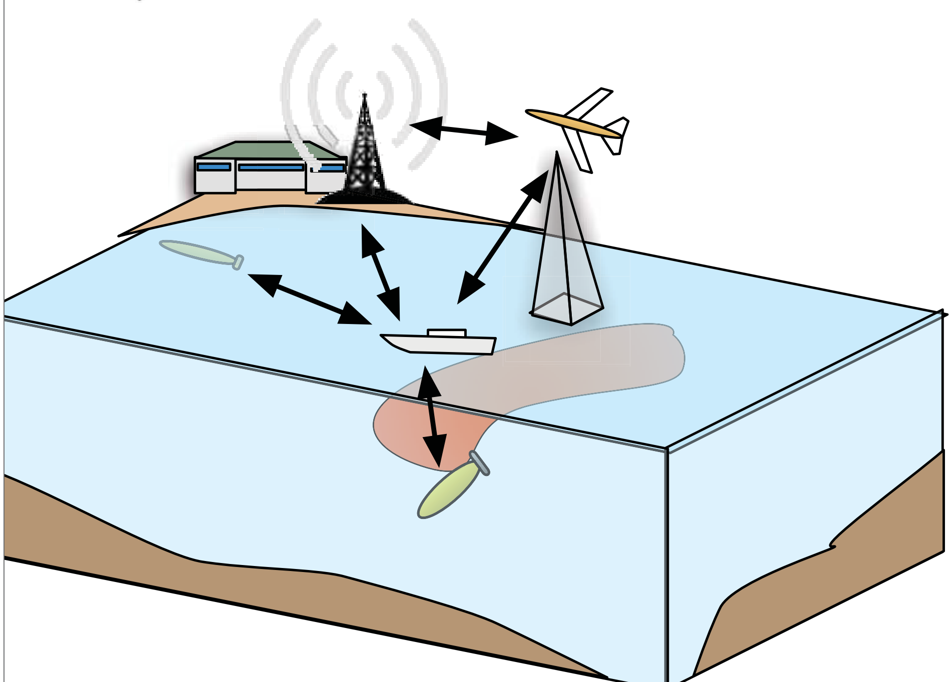
European Space Agency rover testbed



Next Steps: CANON- A Controlled, Agile and Novel Observing Network

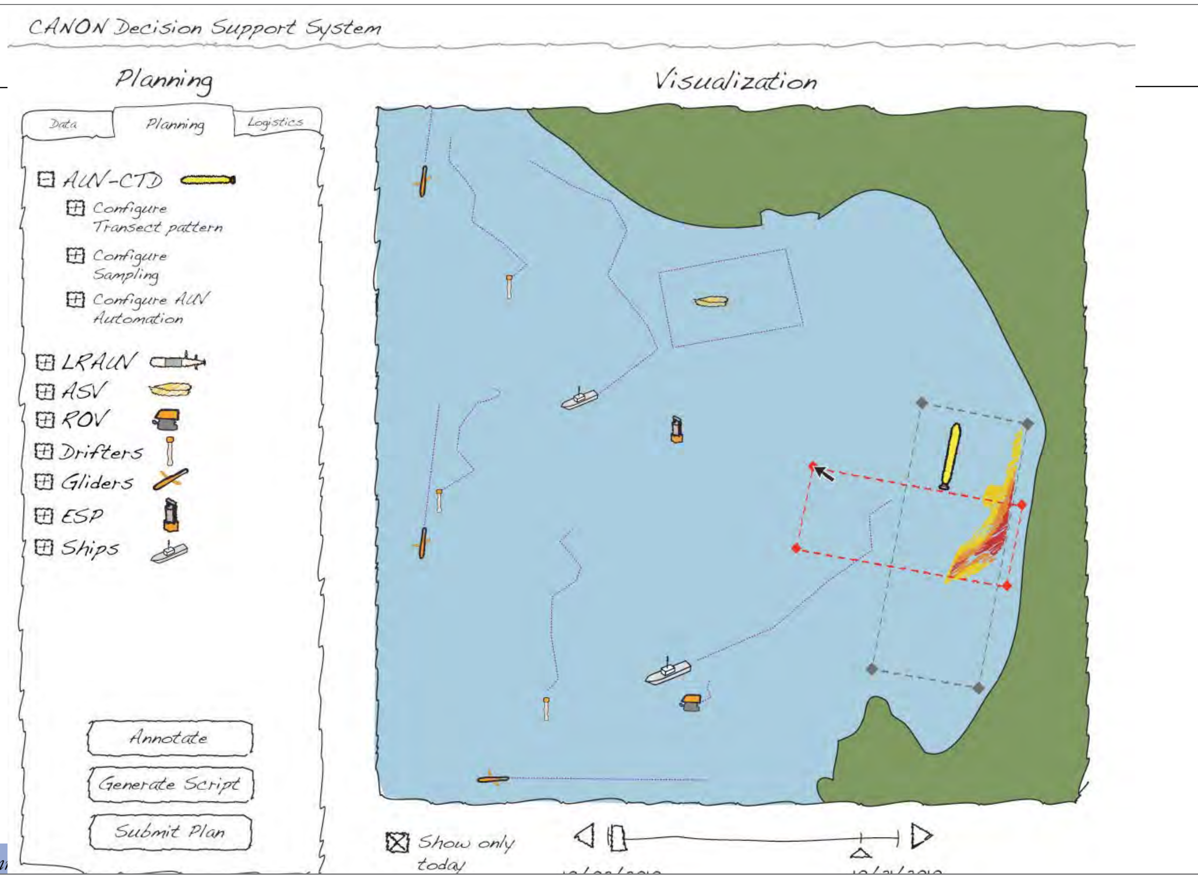


Next Steps: CANON- A Controlled, Agile and Novel Observing Network



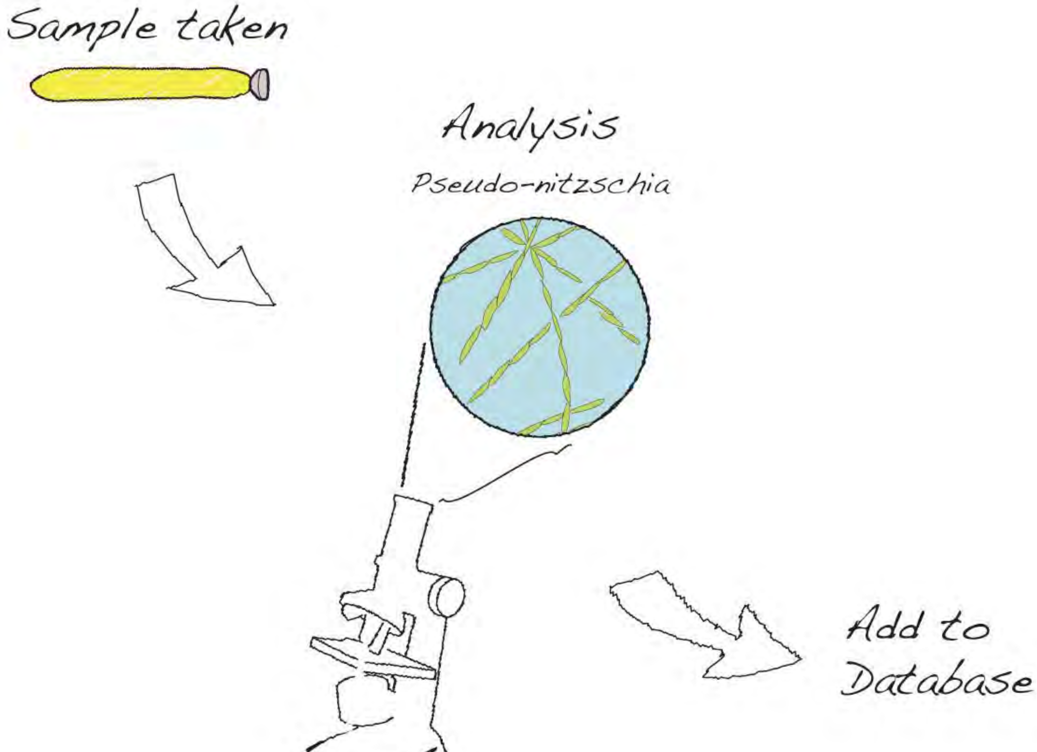
- Mixed-Initiative control from shore/ship
- Loosely coupled multiple *heterogenous* vehicles
- Each vehicle has onboard plan synthesis capability
- Limited information exchange
- Human as a separate 'agent' brings substantial cognitive capability
- Synoptic views are generated by the fusion of disparate map data, combined with onboard autonomy

Decision Support System (DSS) for CANON

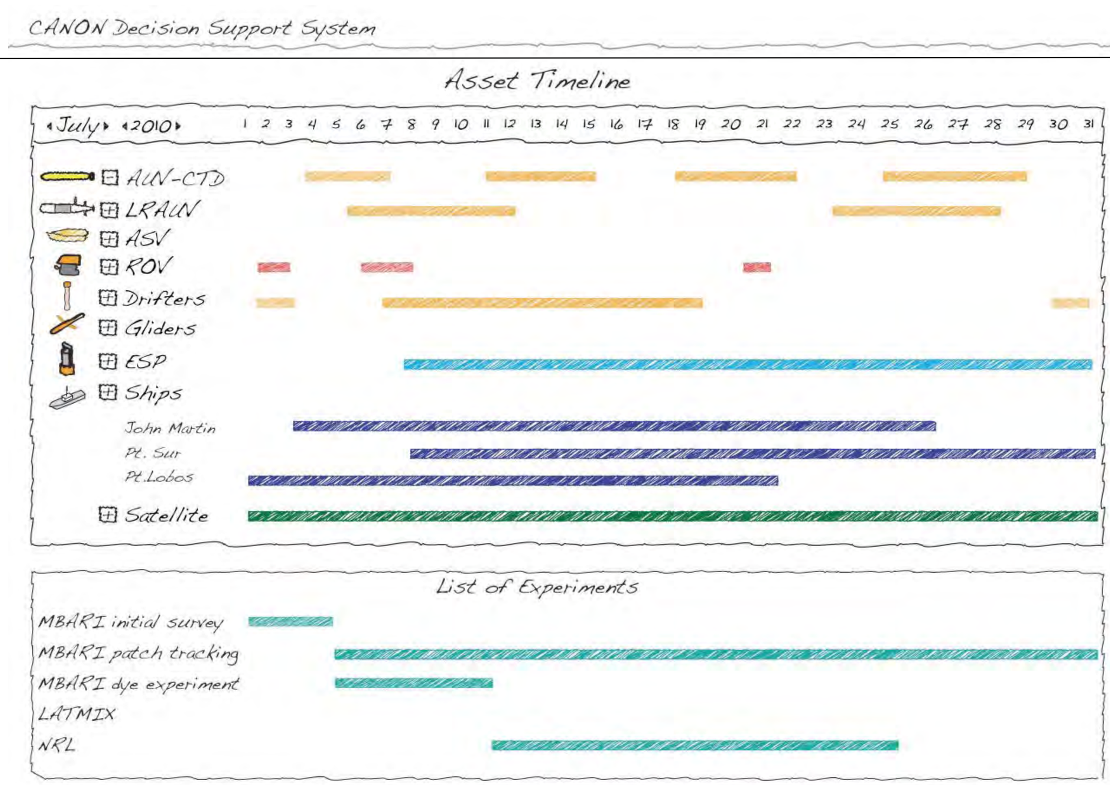


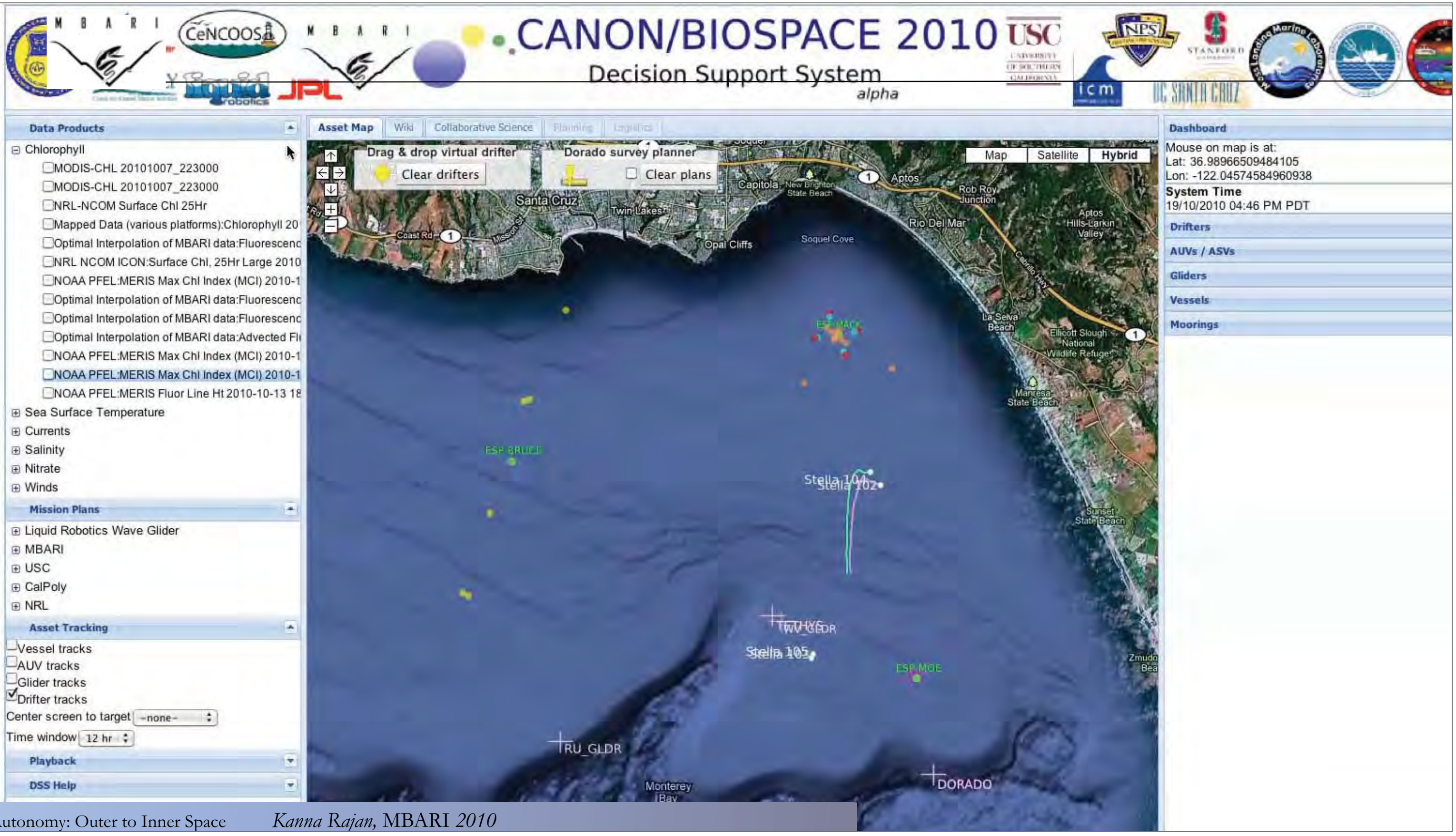
Decision Support System (DSS) for CANON

Decision Support System (DSS) for CANON

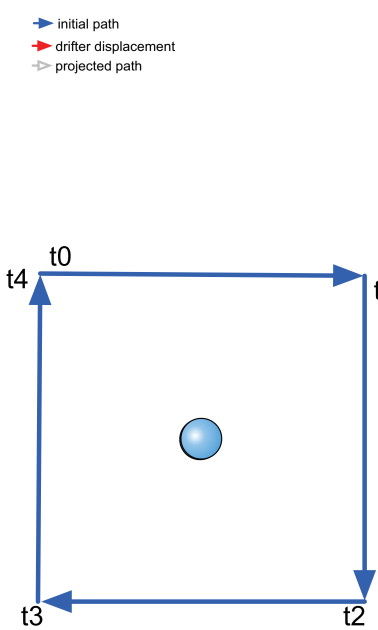


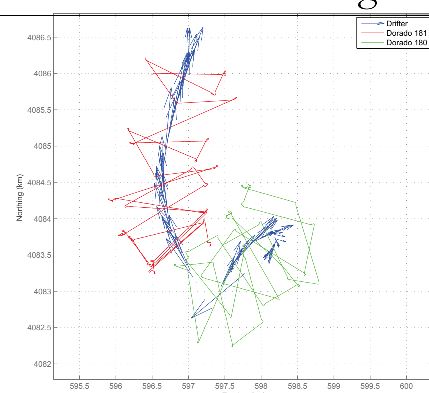
Decision Support System (DSS) for CANON

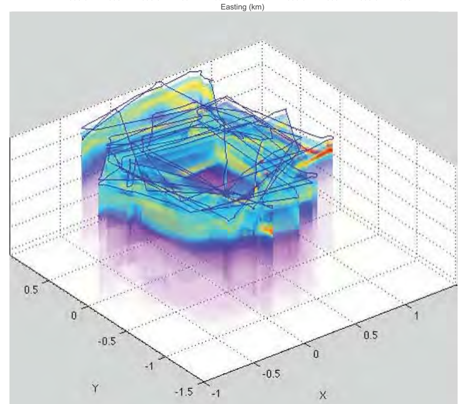




Next Steps: CANON- A Controlled, Agile and Novel Observing Network

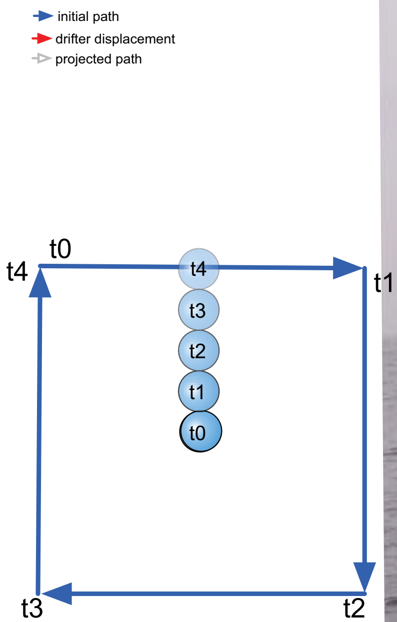


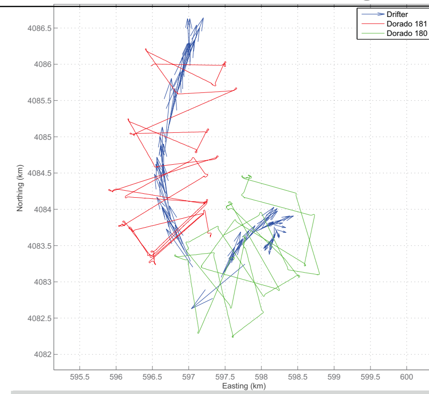


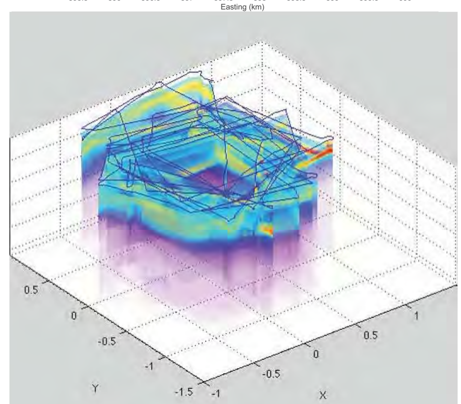


Chl. Fluorescence Oct 2010

Next Steps: CANON- A Controlled, Agile and Novel Observing Network

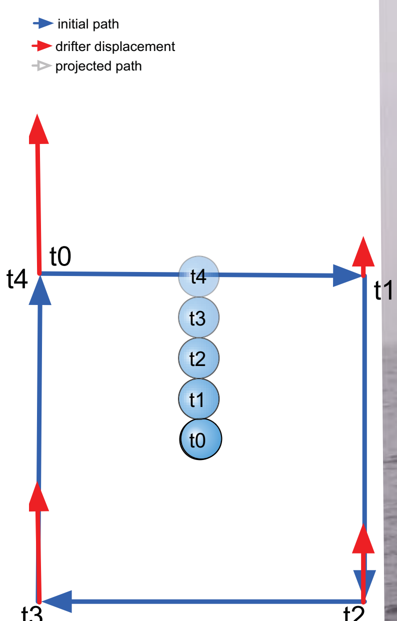


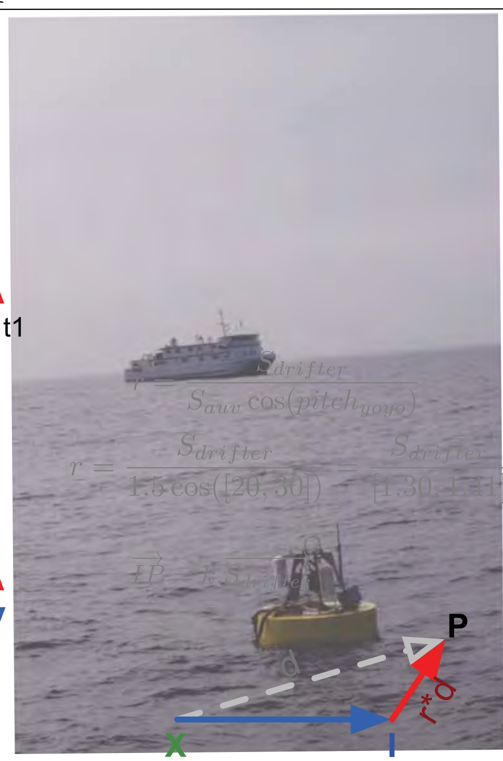


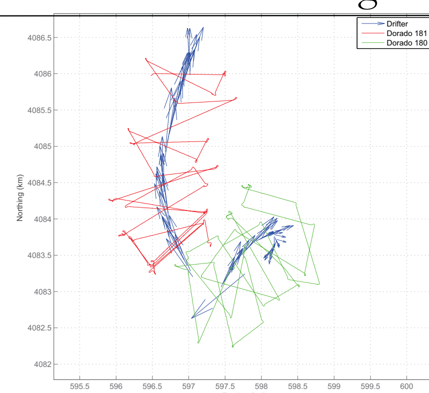


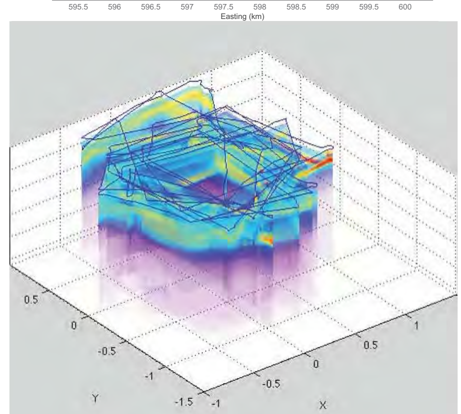
Chl. Fluorescence Oct 2010

Next Steps: CANON- A Controlled, Agile and Novel Observing Network





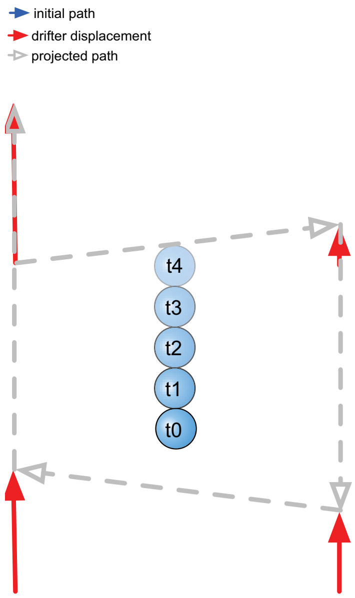


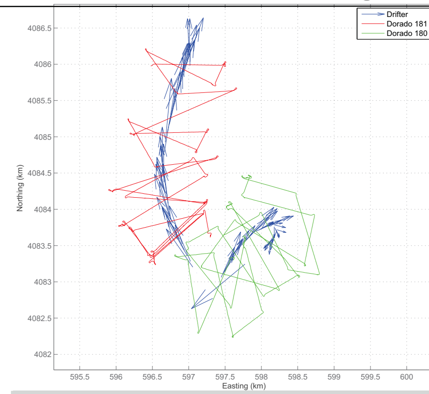


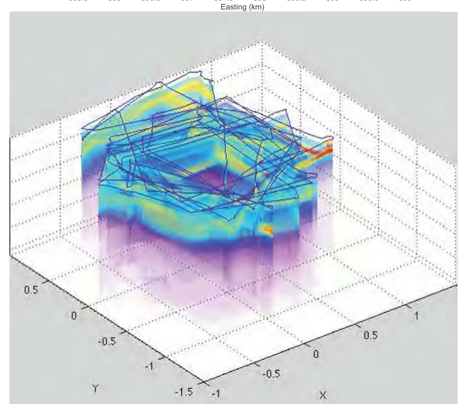
Chl. Fluorescence Oct 2010

Autonomy: Outer to Inner Space *Kanna Rajan*, MBARI *2010*
Friday, December 10, 2010

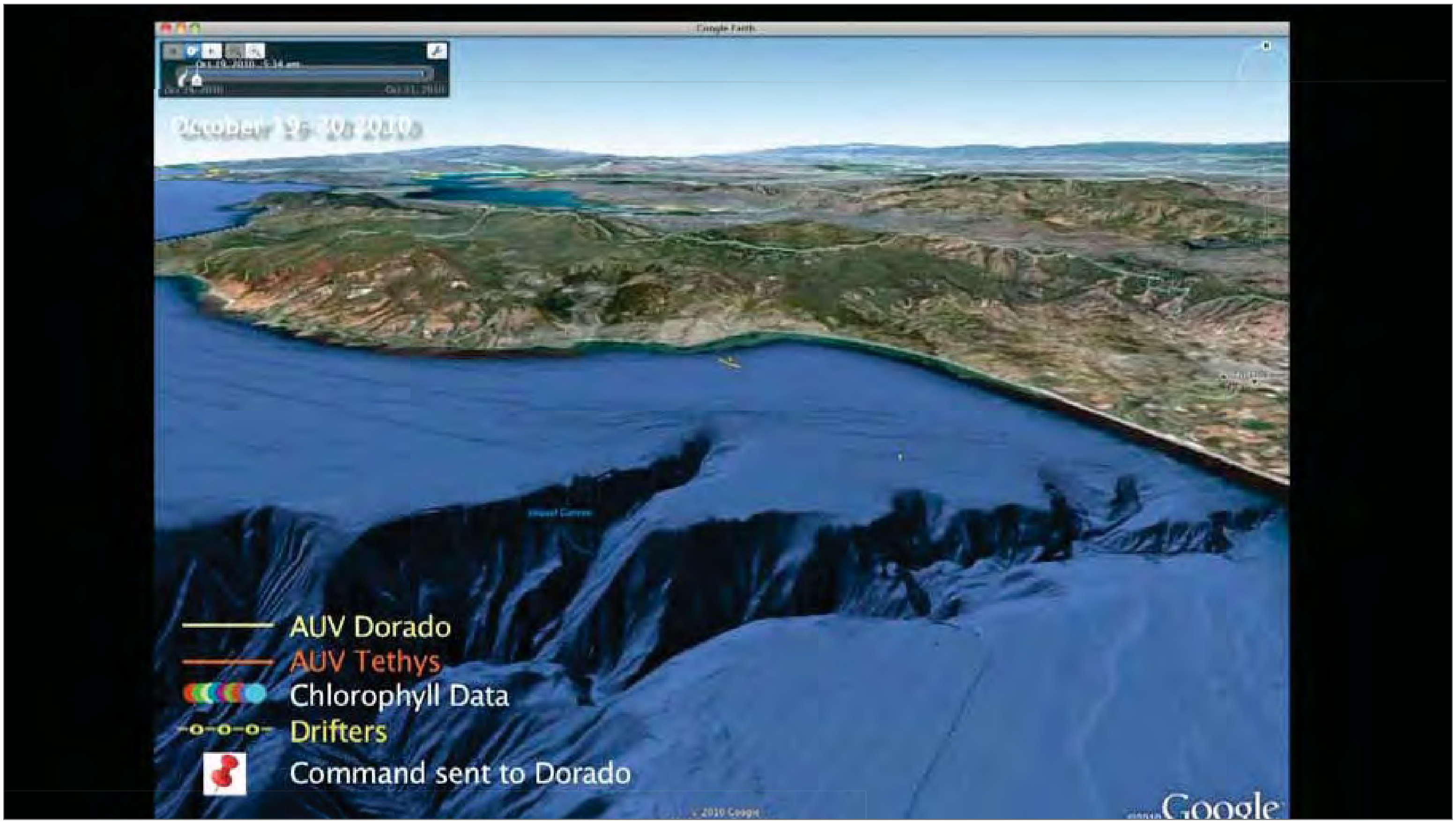
Next Steps: CANON- A Controlled, Agile and Novel Observing Network

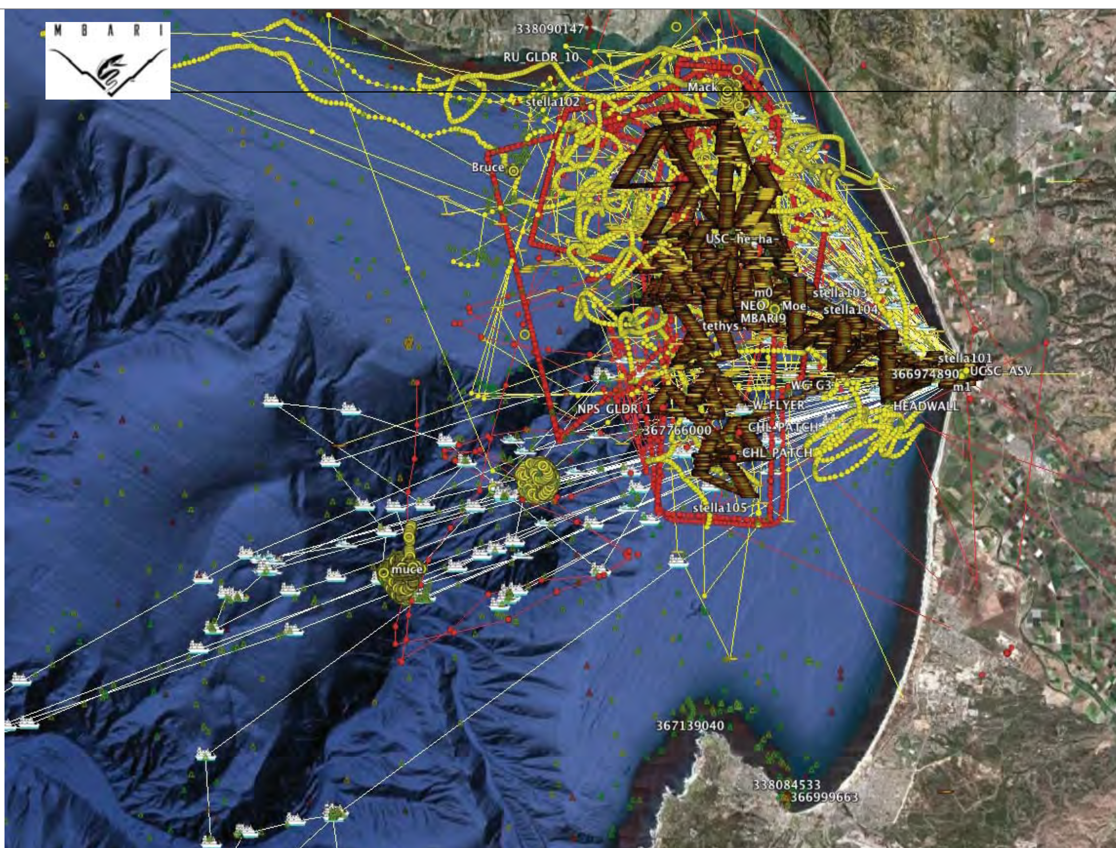






Chl. Fluorescence Oct 2010





Composite of tracks of all CANON assets
for sampling blooms
Oct 9th - 22nd 2010

Concluding Remarks

- The complex coastal ocean requires the ability to sample precisely
  - Ocean models are imprecise and require substantial hand-holding
  - Embodied robots with statistical models coupled to control add scientific value
- We have demonstrated a formal framework for partitioning a complex control problem into multiple Sense-Plan-Act control loops
  - Strong execution semantics
  - Each reactor becomes the executive of the reactors depending on *its* state
  - Coupled state estimation allows modeling dynamic features in the coastal ocean
- Future directions:
  - shore/ship side DSS
  - experiment further system scalability/flexibility
  - diverse solvers for deliberation
  - multi-vehicle shore side control under limited (lossy) communications

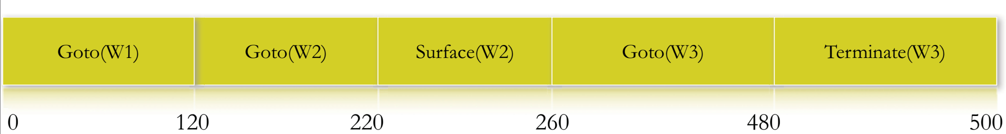
References

- J.Das, F. Py, , T. Maughan, J Ryan , K. Rajan & G. Sukhatme,, "*Simultaneous Tracking and Sampling of Dynamic Oceanographic Features with Autonomous Underwater Vehicles and Lagrangian Drifters"*, Accepted, Intnl. Symp. on Experimental Robotics (ISER), N. Delhi, India, Dec 2010.
- S. Jiménez, F. Py & K. Rajan, "*Learning Identification Models for In-situ Sampling of Ocean features*" Working notes of the RSS'10 Workshop on Active Learning for Robotics. Robotics Systems Sciences, Spain. 2010
- J. Das, K. Rajan, S. Frolov, J. Ryan, F. Py, D. Caron & G. Sukhatme, "*Towards Marine Bloom Trajectory Prediction for AUV Mission Planning*" ICRA, May 2010, Anchorage
- Ryan, J.P., Johnson, S., Sherman, A., Rajan, K., Py, F., Paduan, J., Vrijenhoek, R.,"*Intermediate nepheloid layers as conduits of larval transport*" Limnology & Oceanography: Methods, 2010.
- Py. F, K. Rajan, C. McGann "A Systematic Agent Framework for Situated Autonomous Systems", AAMAS10, Toronto
- Rajan, K, Py, F, McGann, C., Ryan, J., O'Reilly, T., Maughan, T., Roman, B., "*Onboard Adaptive Control of AUVs using Automated Planning and Execution*", Unmanned Underwater Systems Technology conference (UUST), New Hampshire, August 2009.
- McGann, C., Py, F., Rajan, K., Thomas, H. Henthorn, R., McEwen, R. "*A Deliberative Architecture for AUV Control*", ICRA, Pasadena, 2008.
- McGann, C., Py, F., Rajan, K., Ryan, J. Henthorn, R. "*Adaptive Control for Autonomous Underwater Vehicles*", AAAI, Chicago, 2008.
- McGann, C., Py, F., Rajan, K., Thomas, H. Henthorn, R., McEwen, R. "*Preliminary Results for Model-Based Adaptive Control of an Autonomous Underwater Vehicle*", ISER, Athens, 2008.
- McGann, C., Py, F., Rajan, K., Thomas, H. Henthorn, R., McEwen, R. "*Automated Decision Making For a New Class of A*
American Society of Limnology and Oceanography, ASLO/Ocean Sciences, Orlan
- Fox M., Long, D., Py, F., Rajan, K., Ryan, J. "*In-situ Analysis for Intelligent Control*" Pro
Scotland, 2007.
- Bellingham, J, K. Rajan "*Robotics in Remote and Hostile Environments*" *Science* cover artic

- Web Site: **http://www.mbari.org/autonomy/**

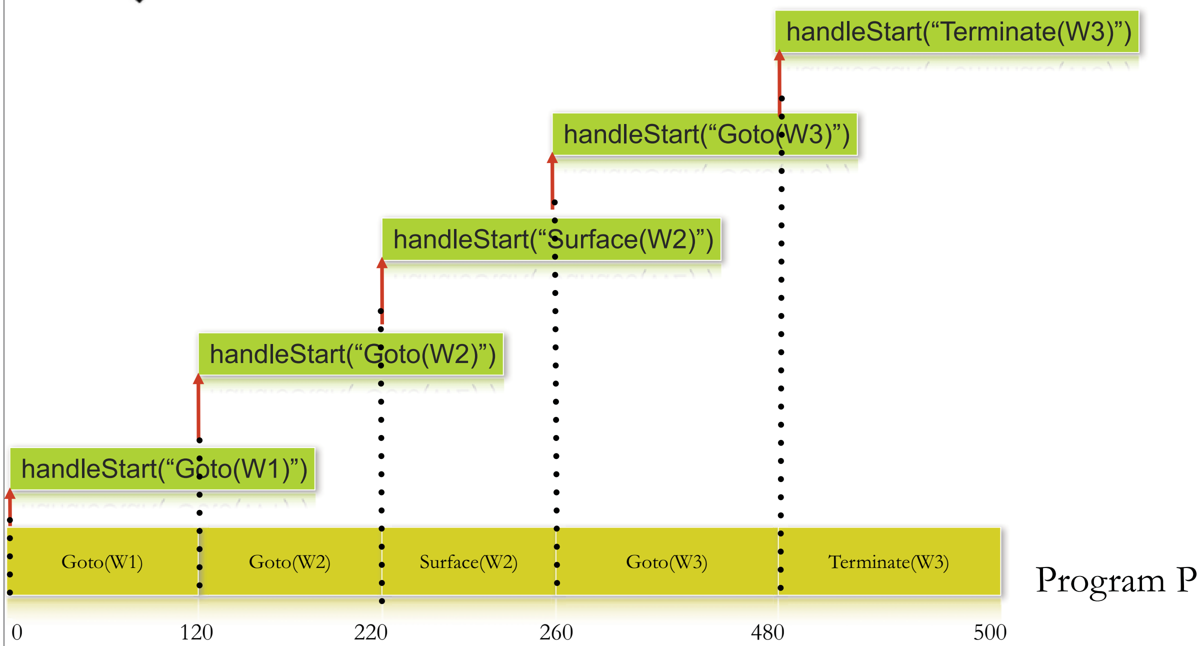
Backup Material

Traditional Approaches for Dispatching Timed Programs

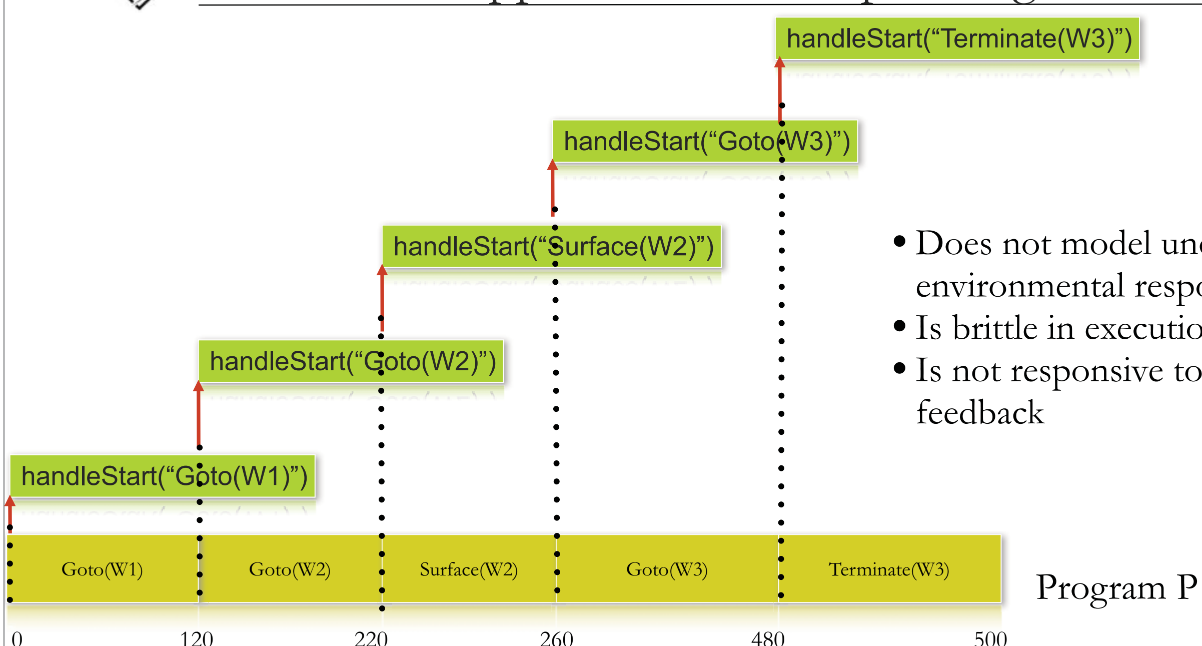


Program P

Traditional Approaches for Dispatching Timed Programs

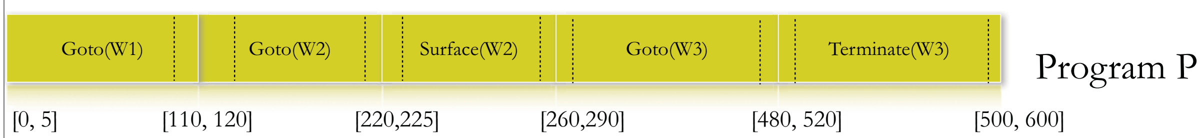


Traditional Approaches for Dispatching Timed Programs

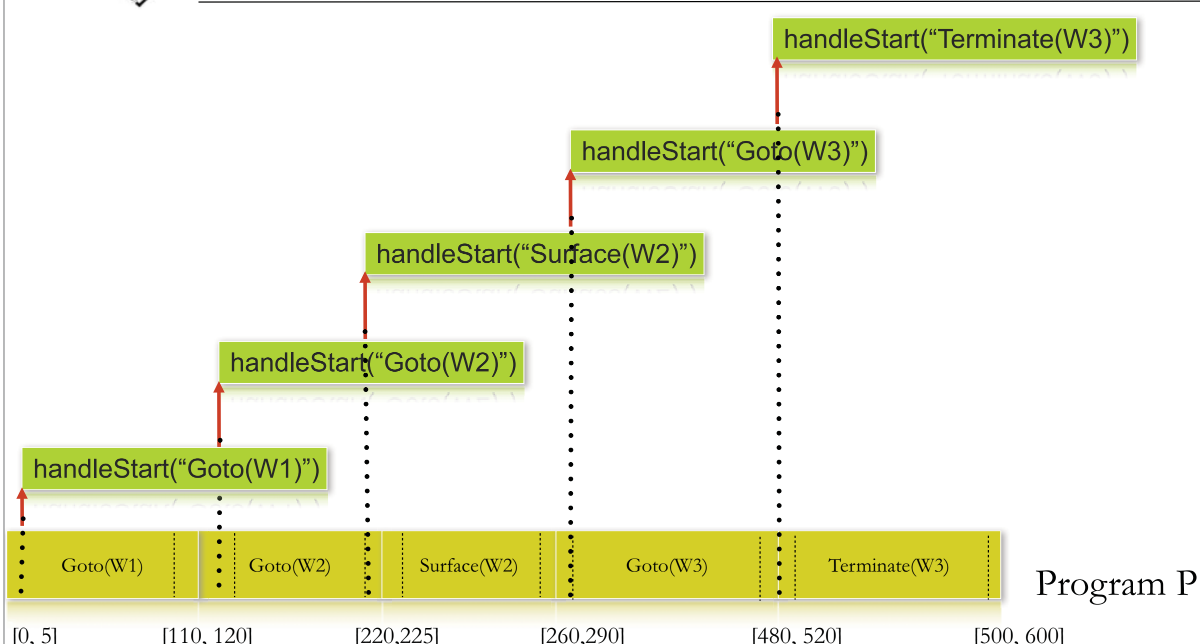


- Does not model uncertainty in action and environmental response
- Is brittle in execution
- Is not responsive to environmental feedback

A less Traditional Approach of Dispatching Timed Programs

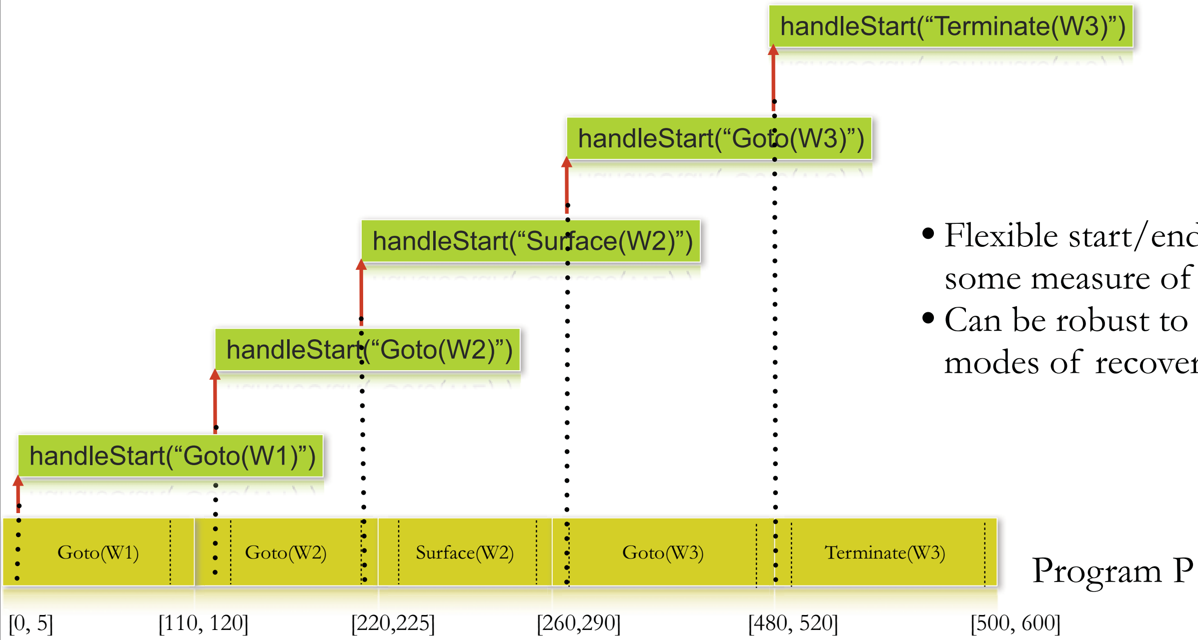


A less Traditional Approach of Dispatching Timed Programs



Autonomy: Outer to Inner Space *Kanna Rajan,* MBARI *2010*
Friday, December 10, 2010

A less Traditional Approach of Dispatching Timed Programs



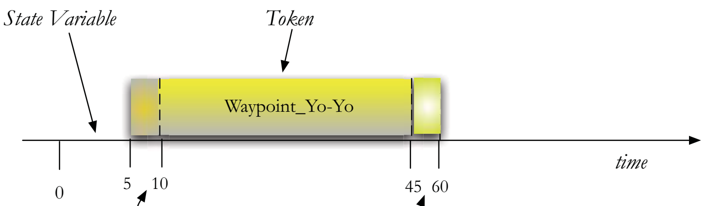
- Flexible start/end times can deal with some measure of uncertainty
- Can be robust to fail-operational modes of recovery

What is Constraint-Based Planning?

- CBP systematizes the use of
  - relationships (real or implied)
  - provides a sound mathematical framework for representing axiomatic equations
  - encapsulates a systematic approach to evolving state
- State-Variable based approaches further decompose the planning problem
  - timelines describe state evolution for pre-specified sub-systems
  - by merging the representations of time with state-variables we can use systematic representations to depict state evolution realistically while still being discrete
- The essential elements of timeline based CBP are:
  - **state variables**: describe evolution of state or a single thread of execution in a concurrent system
  - **tokens**: describes a procedure which instantiates and maintains state
  - **timepoints**: instances of time when a significant change in state is likely to occur
  - **constraints**: explicit representation of relationships between entities within and across timelines

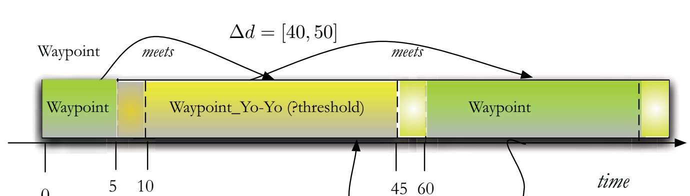
What is Constraint-Based Planning?

- CBP systematizes the use of
  - relationships (real or implied)
  - provides a sound mathematical framework for representing axiomatic equations
  - encapsulates a systematic approach to evolving state
- State-Variable based approaches further decompose the planning problem
  - timelines describe state evolution for pre-specified sub-systems
  - by merging the representations of time with state-variables we can use systematic representations to depict state evolution realistically while still being discrete
- The essential elements of timeline based CBP are:
  - **state variables**: describe evolution of state or a single thread of execution in a concurrent system
  - **tokens**: describes a procedure which instantiates and maintains state
  - **timepoints**: instances of time when a significant change in state is likely to occur
  - **constraints**: explicit representation of relationships between entities within and across timelines

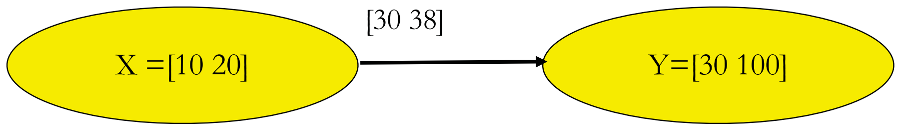


What is Constraint-Based Planning?

- CBP systematizes the use of
  - relationships (real or implied)
  - provides a sound mathematical framework for representing axiomatic equations
  - encapsulates a systematic approach to evolving state
- State-Variable based approaches further decompose the planning problem
  - timelines describe state evolution for pre-specified sub-systems
  - by merging the representations of time with state-variables we can use systematic representations to depict state evolution realistically while still being discrete
- The essential elements of timeline based CBP are:
  - **state variables**: describe evolution of state or a single thread of execution in a concurrent system
  - **tokens**: describes a procedure which instantiates and maintains state
  - **timepoints**: instances of time when a significant change in state is likely to occur
  - **constraints**: explicit representation of relationships between entities within and across timelines

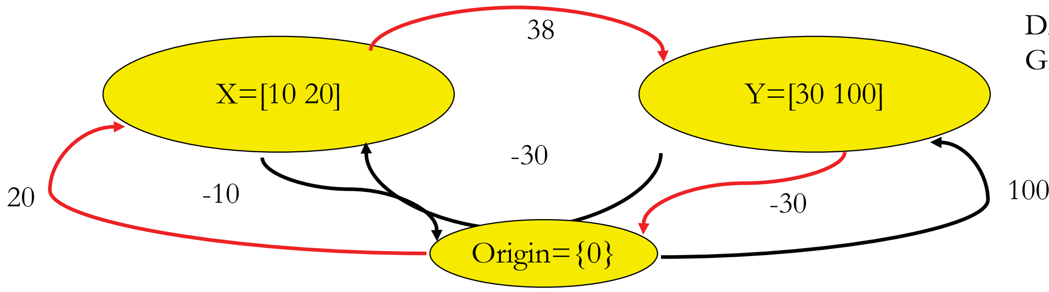


Foundational Representation: Simple Temporal Networks



STN

CONVERSION: Y-X ∈ [30 38] ⇔ Y-X <= 38 ^ X-Y <= -30

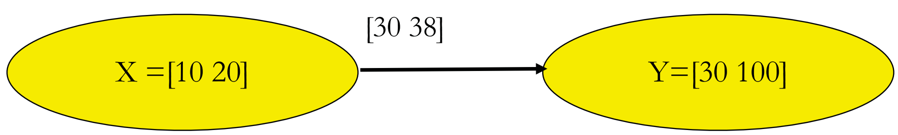


Distance Graph

Upper Bound on Path Length: 20 + 38 -30 = 28

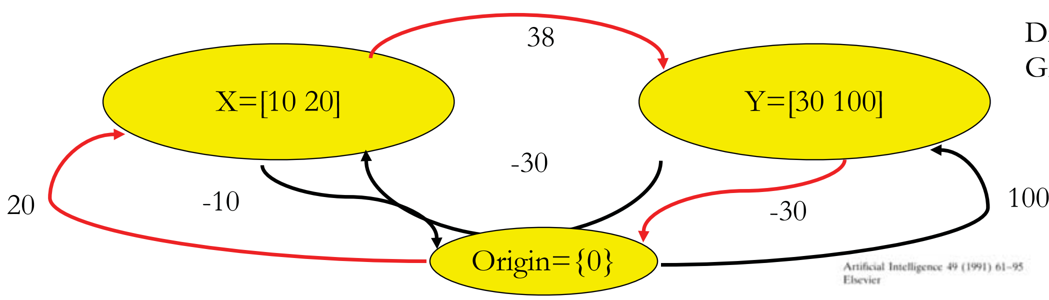
- ❑Fast Incremental Propagation
- ❑Detect Inconsistency with a negative cycle
- ❑Backtrack free search if there is a feasible solution

Foundational Representation: Simple Temporal Networks



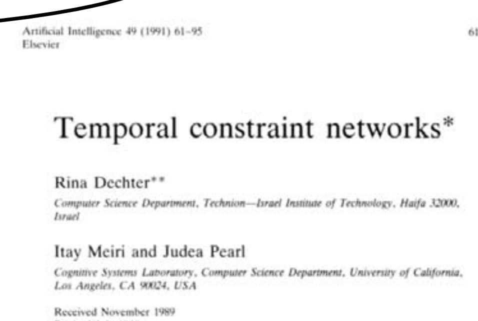
STN

CONVERSION: Y-X ∈ [30 38] ⇔ Y-X <= 38 ^ X-Y <= -30



Distance Graph

Upper Bound on Path Length: 20 + 38 -30 = 28


Artificial Intelligence 49 (1991) 61–95
Elsevier
61

Temporal constraint networks*

Rina Dechter**
Computer Science Department, Technion—Israel Institute of Technology, Haifa 32000, Israel

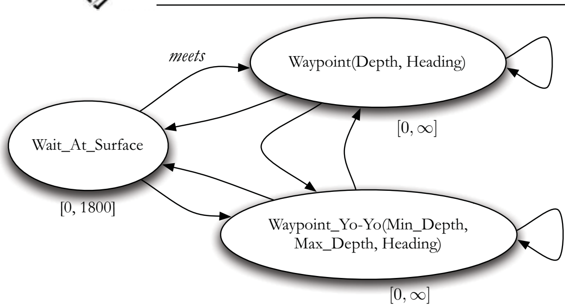
Itay Meiri and Judea Pearl
Cognitive Systems Laboratory, Computer Science Department, University of California, Los Angeles, CA 90024, USA

Received November 1989
Revised July 1990

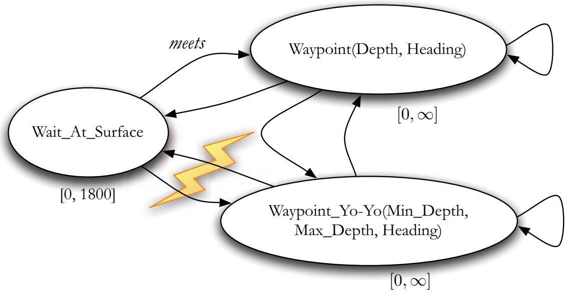
- ❑Fast Incremental Propagation
- ❑Detect Inconsistency with a negative cycle
- ❑Backtrack free search if there is a feasible solution

How does one build Timelines?

How does one build Timelines?

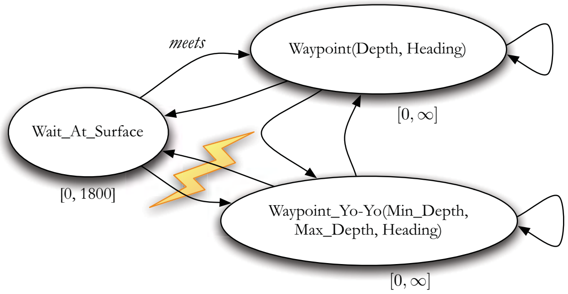


How does one build Timelines?

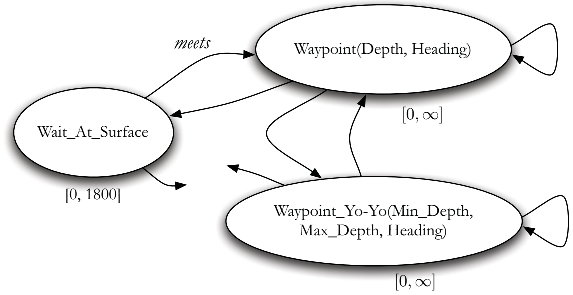


I

How does one build Timelines?

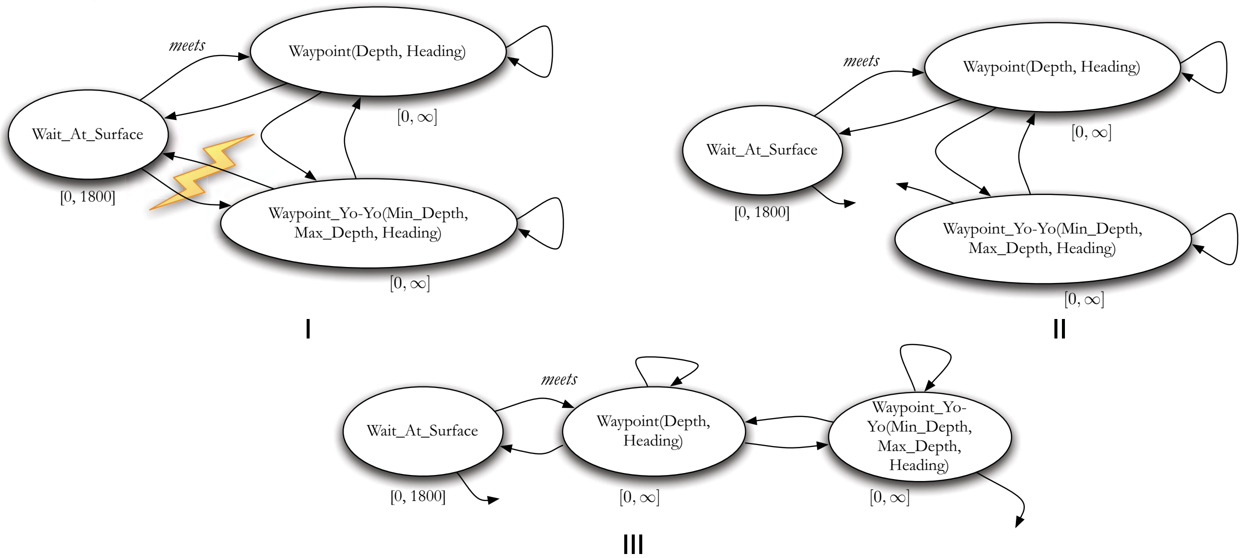


I

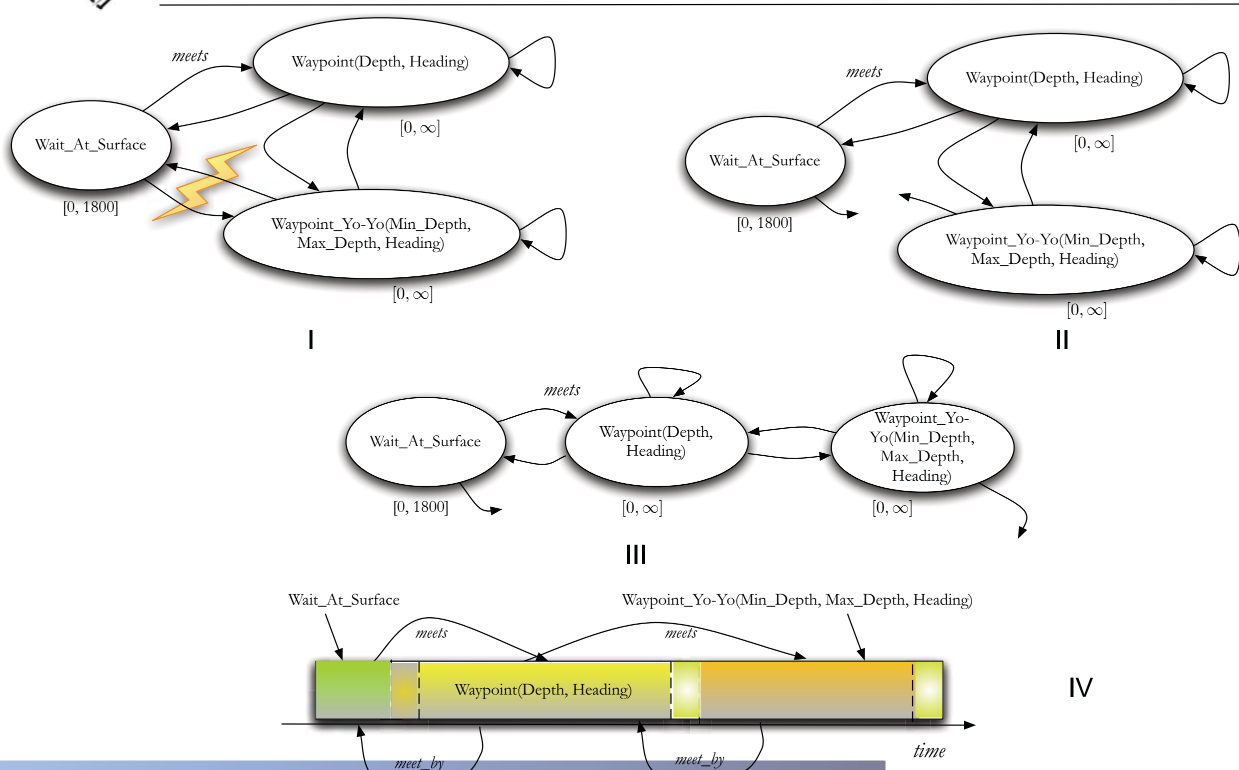


II

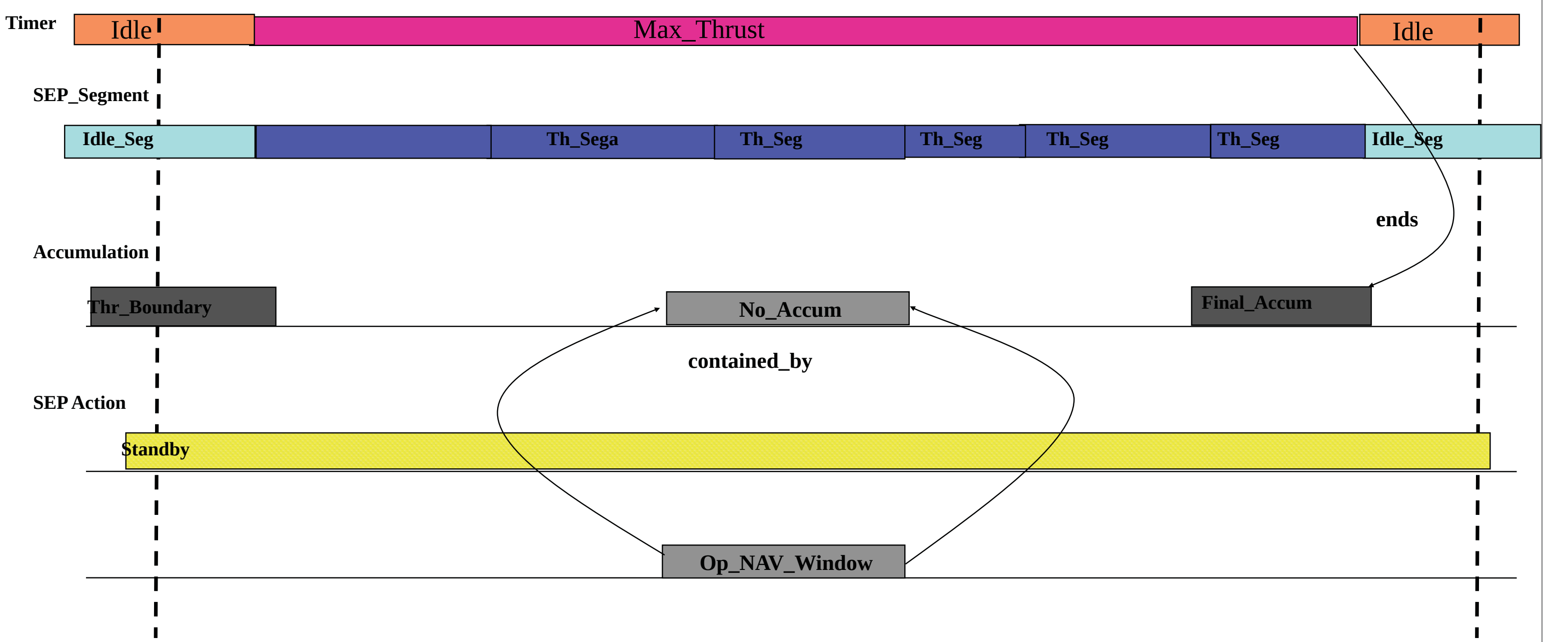
How does one build Timelines?



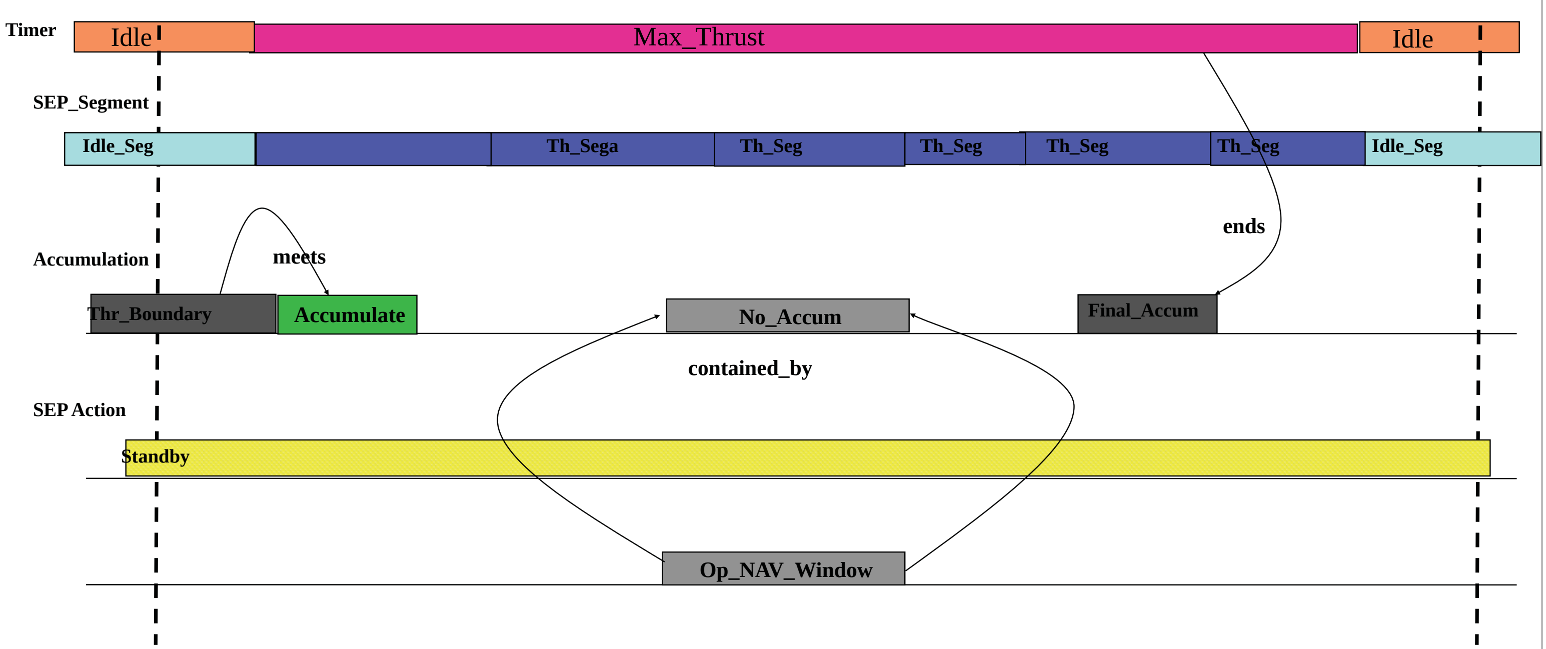
How does one build Timelines?



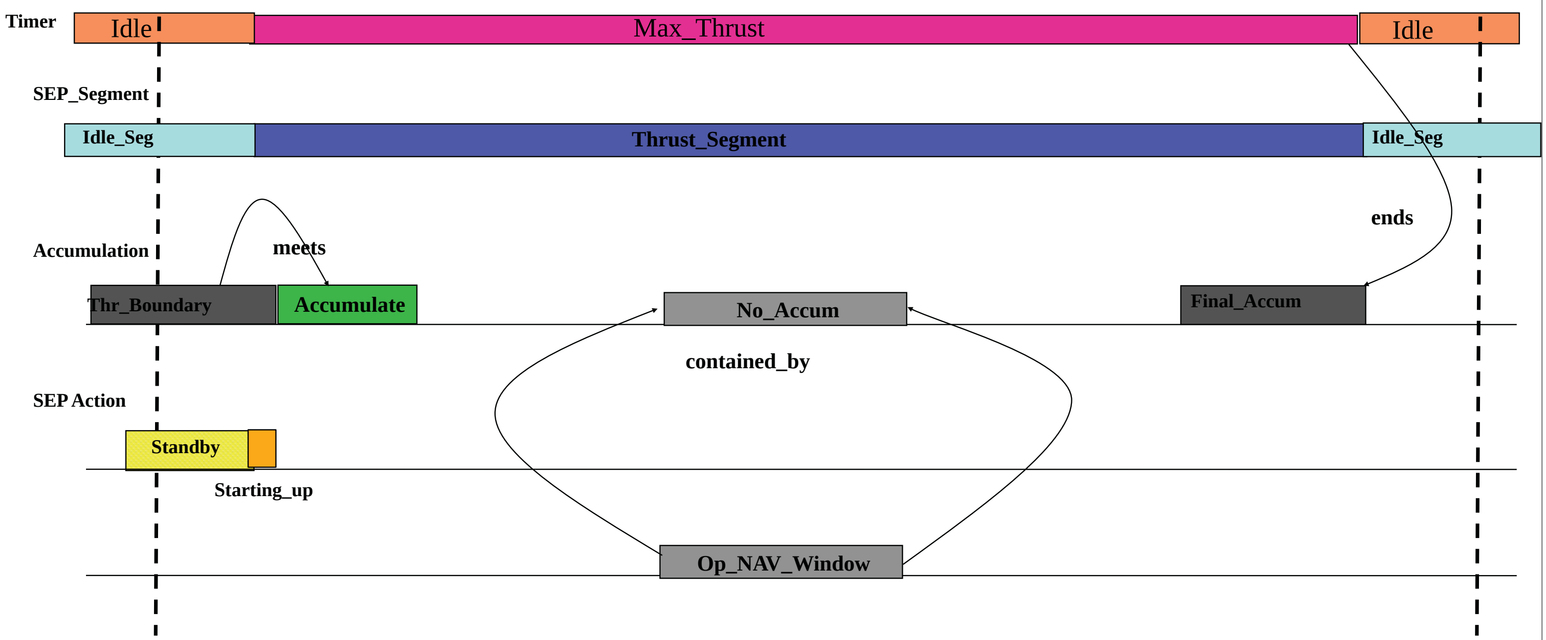
Plan Formulation Example (NASA's Deep Space 1)



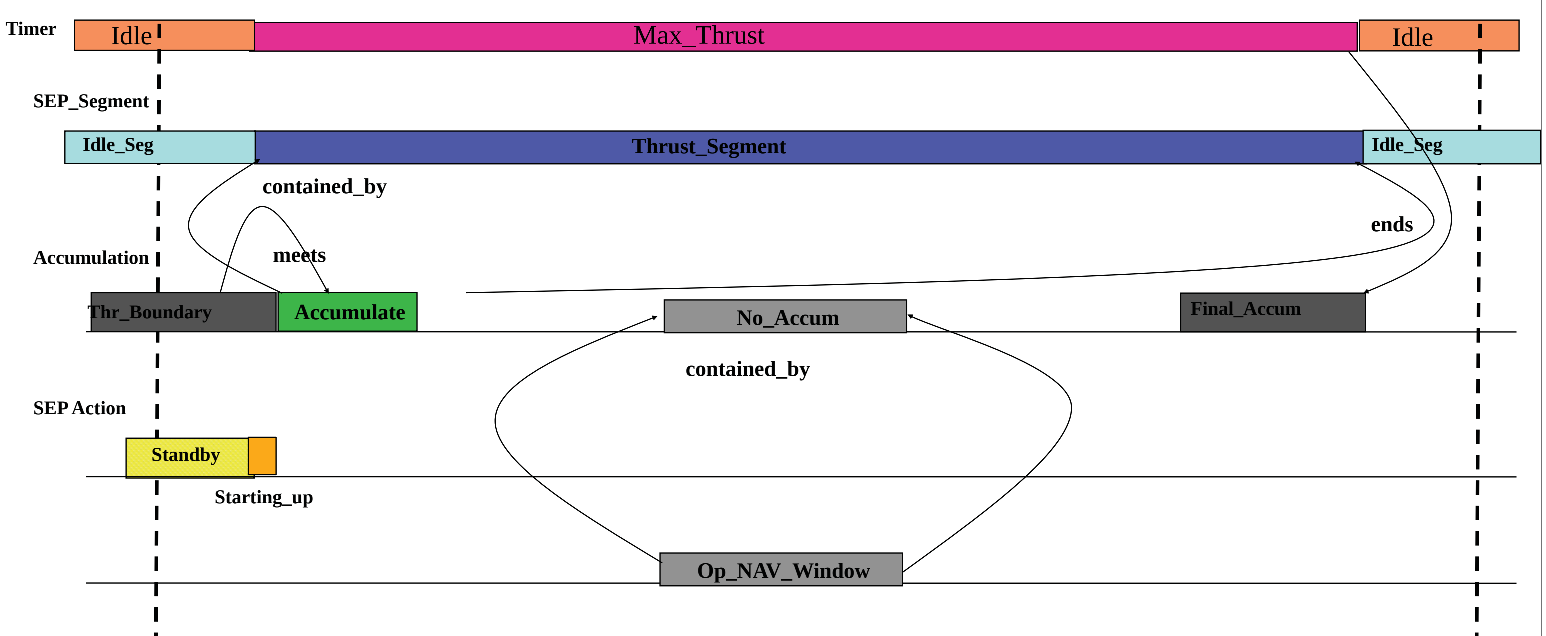
Plan Formulation Example (NASA's Deep Space 1)



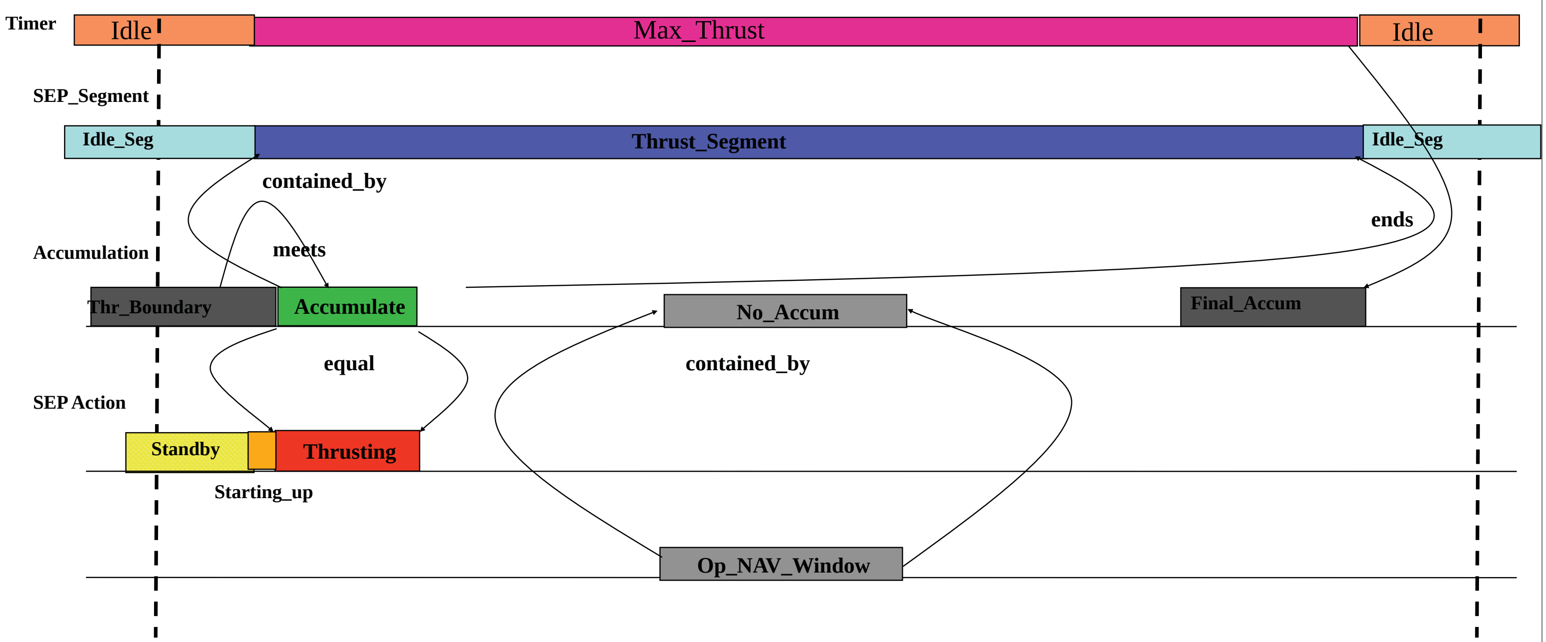
Plan Formulation Example (NASA's Deep Space 1)



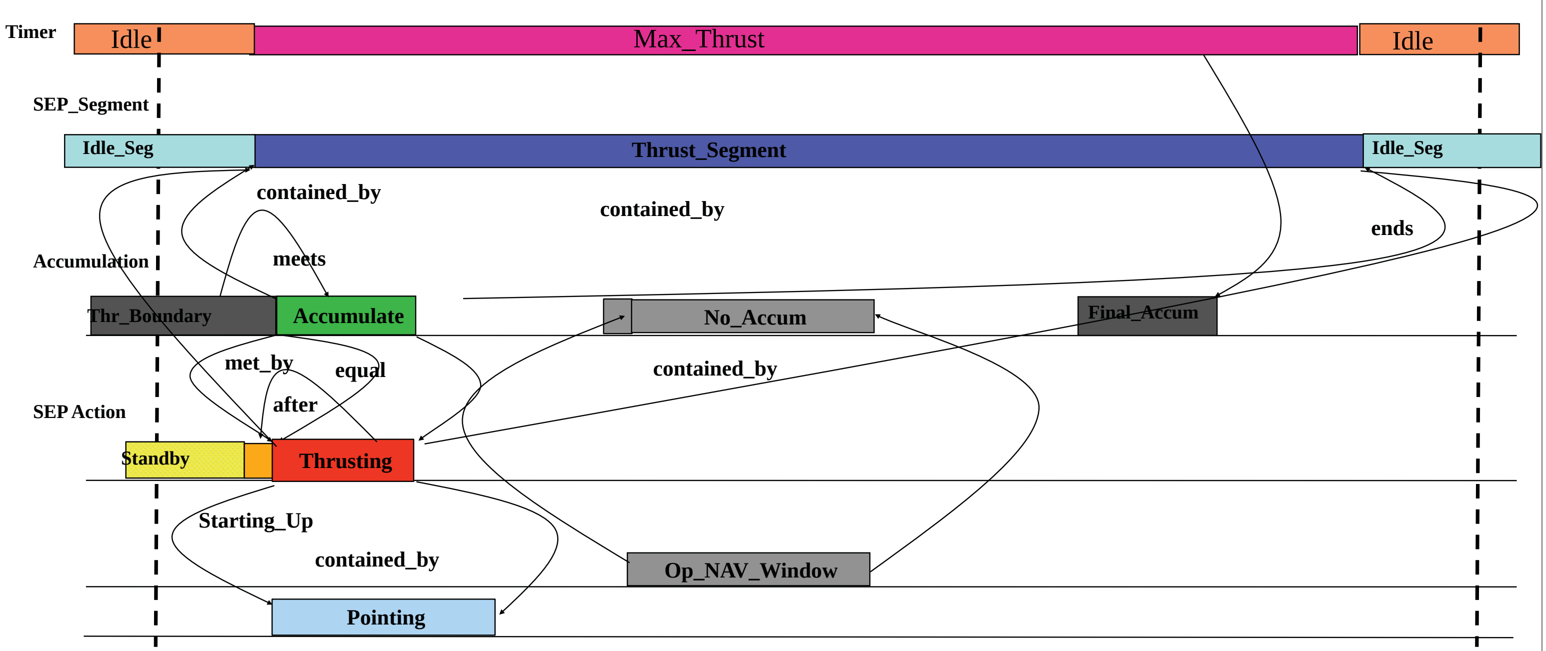
Plan Formulation Example (NASA's Deep Space 1)



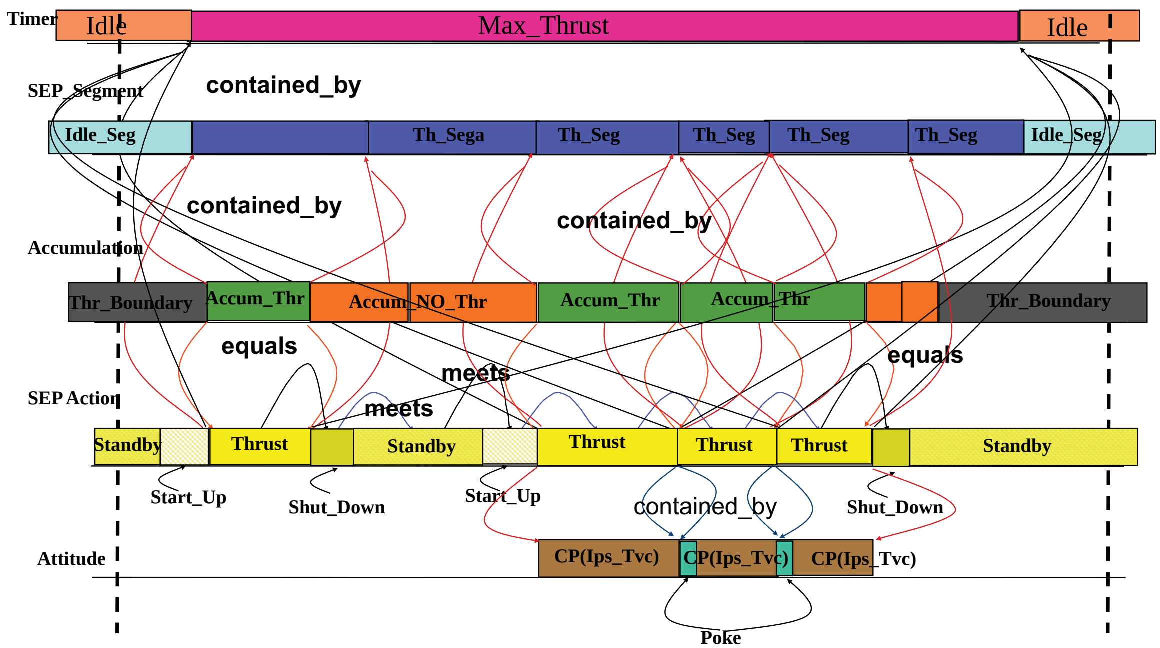
Plan Formulation Example (NASA’s Deep Space 1)



Plan Formulation Example (NASA’s Deep Space 1)



Plan Formulation Example (NASA's Deep Space 1)



What about modeling?

What about modeling?

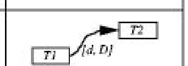
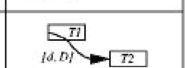
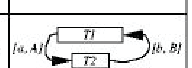
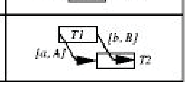
```
class Front extends
AgentTimeline {
  predicate None {}

  predicate Info {
    float temperature;
    DEPTH depth;
    DEPTH mapDepth;
    eq(duration, 1);
  }

  predicate Begin {}

  predicate Search {
    float temperature;
    DEPTH depth;
    NORTHING xTo;
    EASTING yTo;
    bool frontDetected;
    NORTHING xFront;
    EASTING yFront;
  }
  predicate Map {
    NORTHING xFront;
    EASTING yFront;
    float   gulpSeparation;
  }
 }
```

```
Front::Map {
  float distanceToFrom, distanceToTo;
  bool closeToFrom, closeToTo;
  float x1, y1, x2, y2;

  contained_by(FrontTracker.Track trk);

  calcDistance(distanceToFrom, trk.xFrom, trk.yFrom, xFront, yFron
  testLEQ(closeToFrom, distanceToFrom, trk.moveIncrement);

  calcDistance(distanceToTo, trk.xTo, trk.yTo, xFront, yFront);
  testLEQ(closeToTo, distanceToTo, trk.moveIncrement);

  if( closeToFrom==false ) {
    float ratioFrom, dxToFrom, dyToFrom, dx2, dy2;

    addEq(trk.xFrom, dxToFrom, xFront);
    addEq(trk.yFrom, dyToFrom, yFront);
    addEq(x2, dx2, xFront);
    addEq(y2, dy2, yFront);
    mulEq(trk.moveIncrement, ratioFrom, distanceToFrom);
    mulEq(dx2, ratioFrom, dxToFrom);
    mulEq(dy2, ratioFrom, dyToFrom);
  }
  if( closeToFrom==true ) {
    eq(x2, trk.xFrom);
    eq(y2, trk.yFrom);
  }
..............
```


What about modeling?

```
class Front extends
AgentTimeline {
  predicate None {}

  predicate Info {
    float temperature;
    DEPTH depth;
    DEPTH mapDepth;
    eq(duration, 1);
  }

  predicate Begin {}

  predicate Search {
    float temperature;
    DEPTH depth;
    NORTHING xTo;
    EASTING yTo;
    bool frontDetected;
    NORTHING xFron
    EASTING yFront;
  }
  predicate Map {
    NORTHING xFron.,
    EASTING yFront;
    float   gulpSeparation;
  }
 }
```

Allen Algebra*

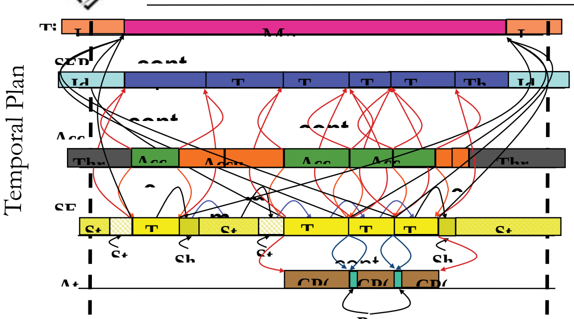
Temporal Relation	Inverse Temporal Relation	Topology
T1 before (d D) T2	T2 after (d D) T1	
T1 starts_before (d D) T2	T2 starts_after (d D) T1	
T1 ends_before (d D) T2	T2 ends_after (d D) T1	
T1 starts_before_end (d D) T2	T2 ends_after_start (d D) T1	
T1 contains ((a A) (b B)) T2	T2 contained_by ((a A) (b B)) T1	
T1 parallels ((a A) (b B)) T2	T2 paralleled_by ((a A) (b B)) T1	

```
Front::Map {
  float distanceToFrom, distanceToTo;
  bool closeToFrom, closeToTo;
  float x1, y1, x2, y2;

  contained_by(FrontTracker.Track trk);

  calcDistance(distanceToFrom, trk.xFrom, trk.yFrom, xFront, yFron
  testLEQ(closeToFrom, distanceToFrom, trk.moveIncrement);

  calcDistance(distanceToTo, trk.xTo, trk.yTo, xFront, yFront);
  testLEQ(closeToTo, distanceToTo, trk.moveIncrement);

  if( closeToFrom==false ) {
    float ratioFrom, dxToFrom, dyToFrom, dx2, dy2;

    addEq(trk.xFrom, dxToFrom, xFront);
    addEq(trk.yFrom, dyToFrom, yFront);
    addEq(x2, dx2, xFront);
    addEq(y2, dy2, yFront);
    mulEq(trk.moveIncrement, ratioFrom, distanceToFrom);
    mulEq(dx2, ratioFrom, dxToFrom);
    mulEq(dy2, ratioFrom, dyToFrom);
  }
  if( closeToFrom==true ) {
    eq(x2, trk.xFrom);
    eq(y2, trk.yFrom);
  }
..............
```

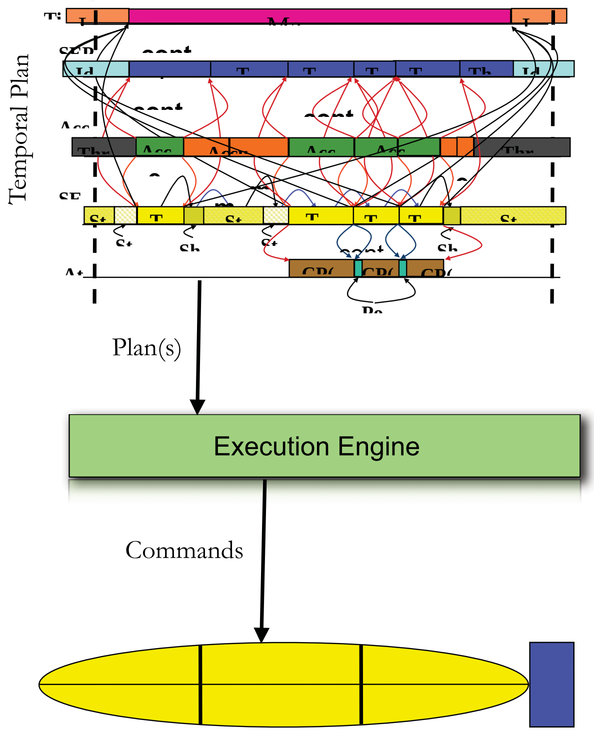
J. Allen, "Towards a General Theory of Action and Time," Artificial Intelligence, vol. 23(2), p. 123154, 1984

So how does one execute a (temporal) plan?

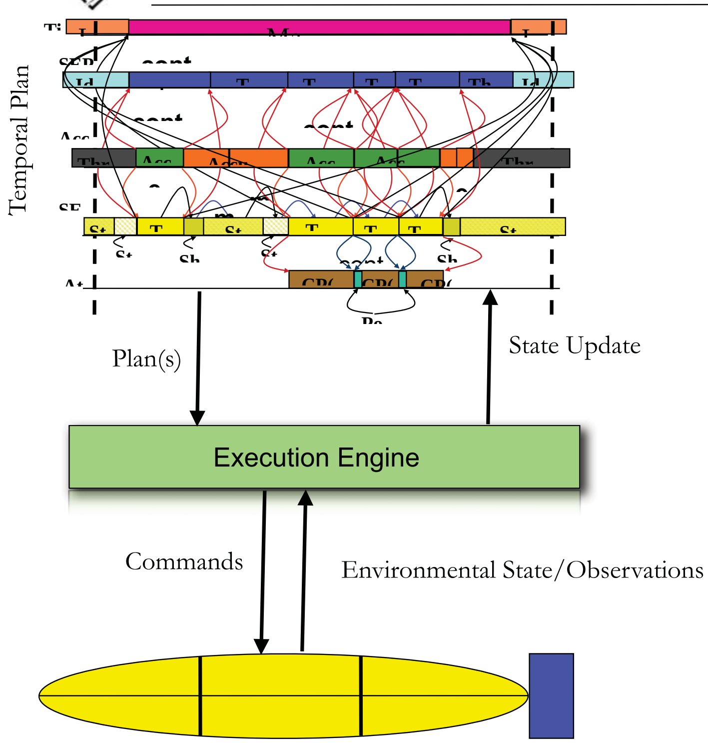
So how does one execute a (temporal) plan?



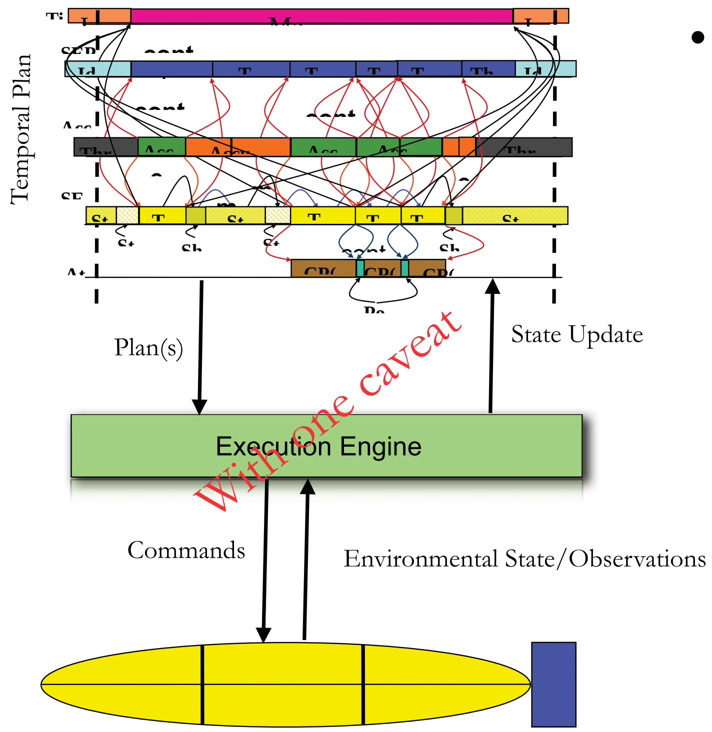
So how does one execute a (temporal) plan?



So how does one execute a (temporal) plan?

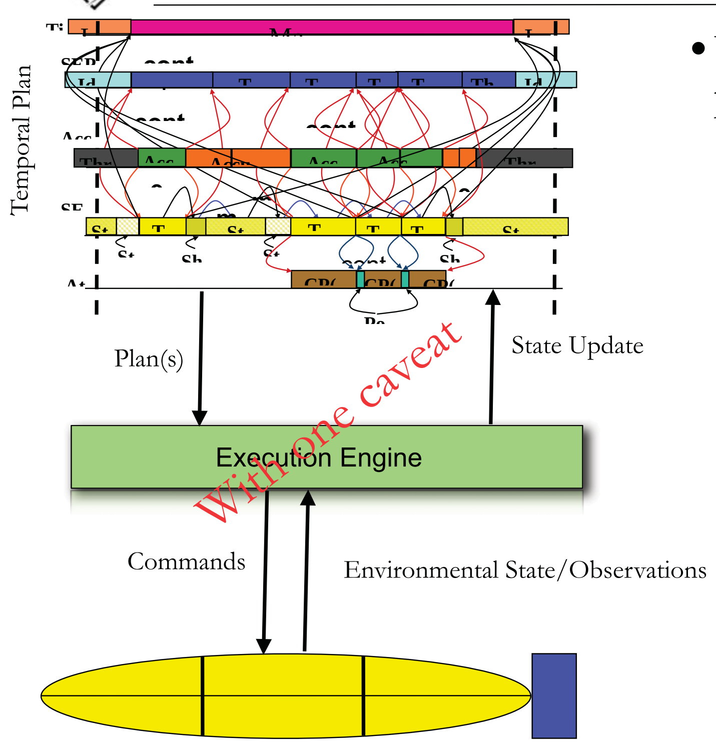


So how does one execute a (temporal) plan?

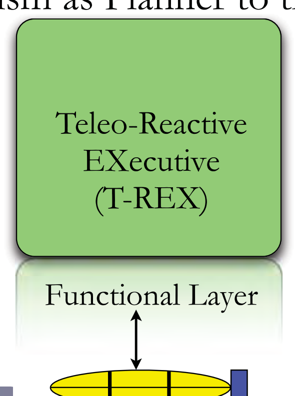


- Use a <u>single</u> temporal database to enforce planning constraints & for dispatching
  - Solves dispatachability issues
  - Retains causal structure for "reasoning" by the executor
  - Execution engine accesses the same plan causal structure and uses same inference mechanism as Planner to the database

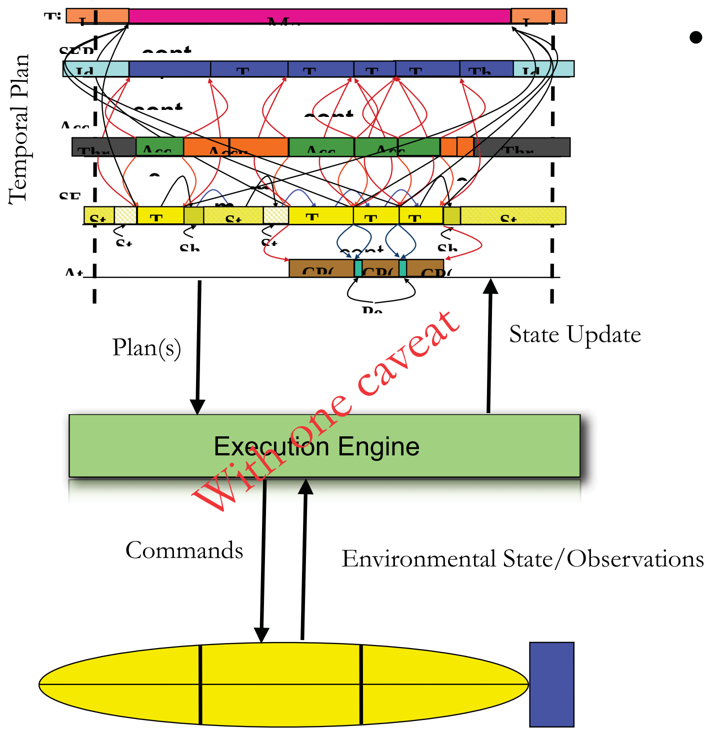
So how does one execute a (temporal) plan?



- Use a <u>single</u> temporal database to enforce planning constraints & for dispatching
  - Solves dispatachability issues
  - Retains causal structure for "reasoning" by the executor
  - Execution engine accesses the same plan causal structure and uses same inference mechanism as Planner to the database



So how does one execute a (temporal) plan?



- Use a <u>single</u> temporal database to enforce planning constraints & for dispatching
  - Solves dispatachability issues
  - Retains causal structure for "reasoning" by the executor
  - Execution engine accesses the same plan causal structure and uses same inference mechanism as Planner to the database