Marine Systems & Robotics
The Long Way to Persistent Autonomy in Underwater Robotics

Prof. Dr. Francesco Maurelli

http://impact.uni-bremen.de/

Current Autonomous Underwater Vehicles

- Great at survey missions
- Pre-planned path
- LBL localization system
- Limited to no autonomy

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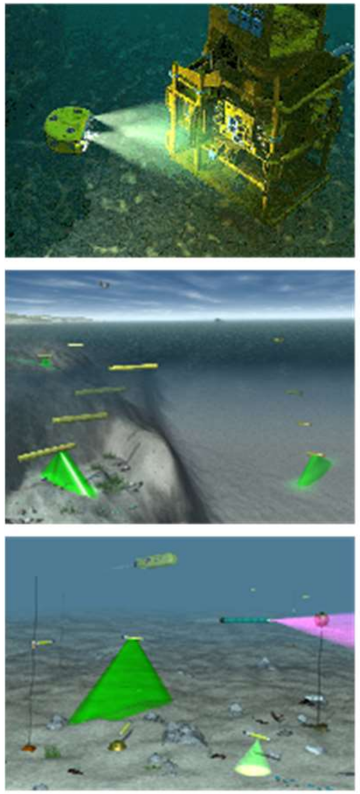
Persistent autonomy



- operate successfully while unsupervised
- operate for extended lengths of time
- operate in environments which are not completely known
- apart goals in response to unexpected events and disturbances
- recover from errors in task execution

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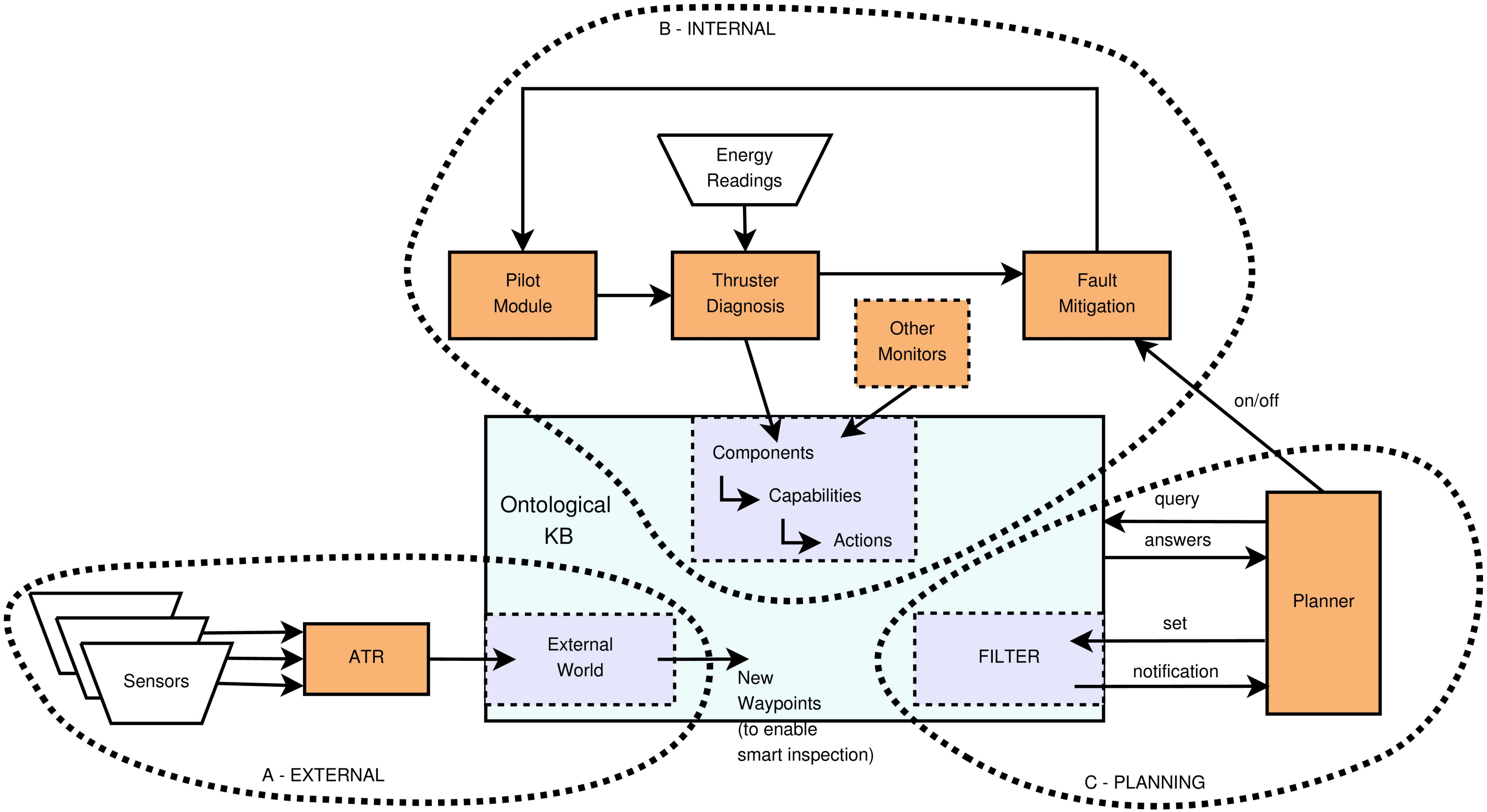
The role of the knowledge base



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Subsystem A - External

- Signal and sensor data processing
- (Deep) Learning
- Knowledge Representation and Reasoning

- F Maurelli, Z Saigol, G Papadimitriou, T Larkworthy, V De Carolis, D Lane, **Probabilistic approaches in ontologies: joining semantics and uncertainty for AUV persistent autonomy**; Proceedings of IEEE-MTS Oceans'13, San Diego, USA

- F Maurelli, Z Saigol, D Lane, **Cognitive knowledge representation under uncertainty for autonomous underwater vehicles**; IEEE ICRA'14 Hong Kong, Workshop on Persistent Autonomy for Underwater Robotics

- F Maurelli, S Krupiński, **A semantic-aided particle filter approach for AUV localization,** 2018 OCEANS-MTS/IEEE Kobe

- L Mucolli, S Krupinski, SA Mehdi, S Mazhar, F Maurelli, **Detecting cracks in underwater concrete structures: an unsupervised learning approach based on local feature clustering,** OCEANS 2019 MTS/IEEE SEATTLE

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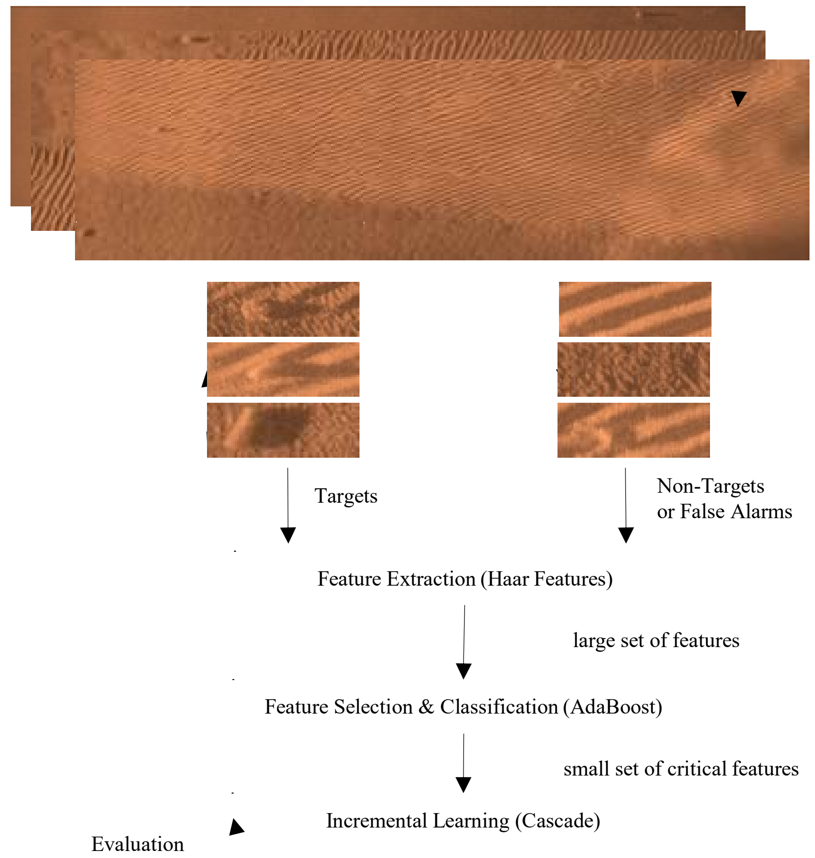
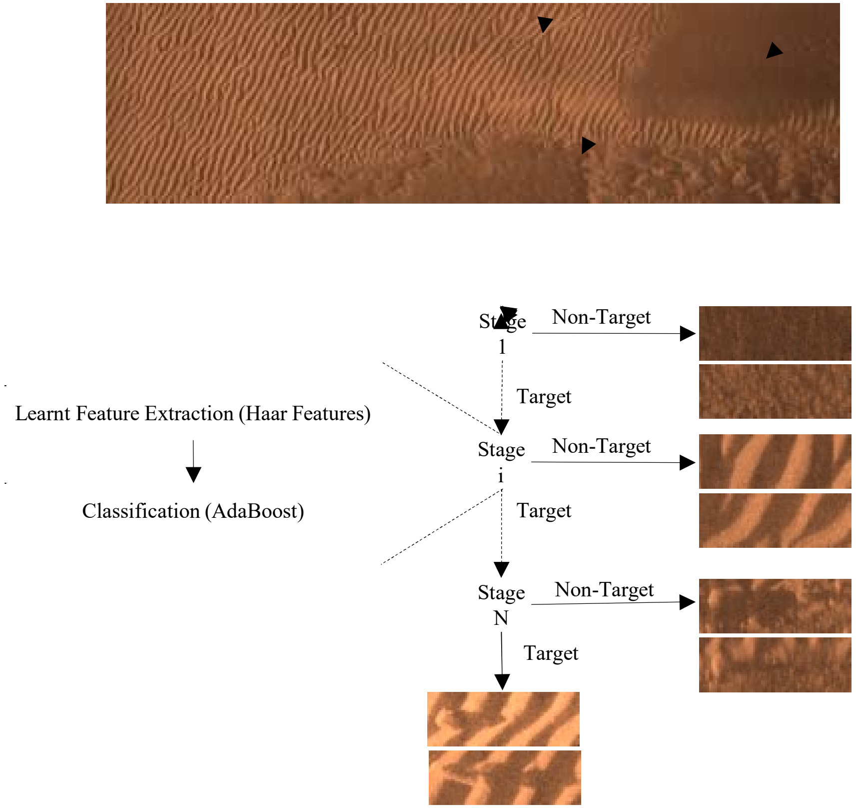
Sensor Processing – sidescan sonar

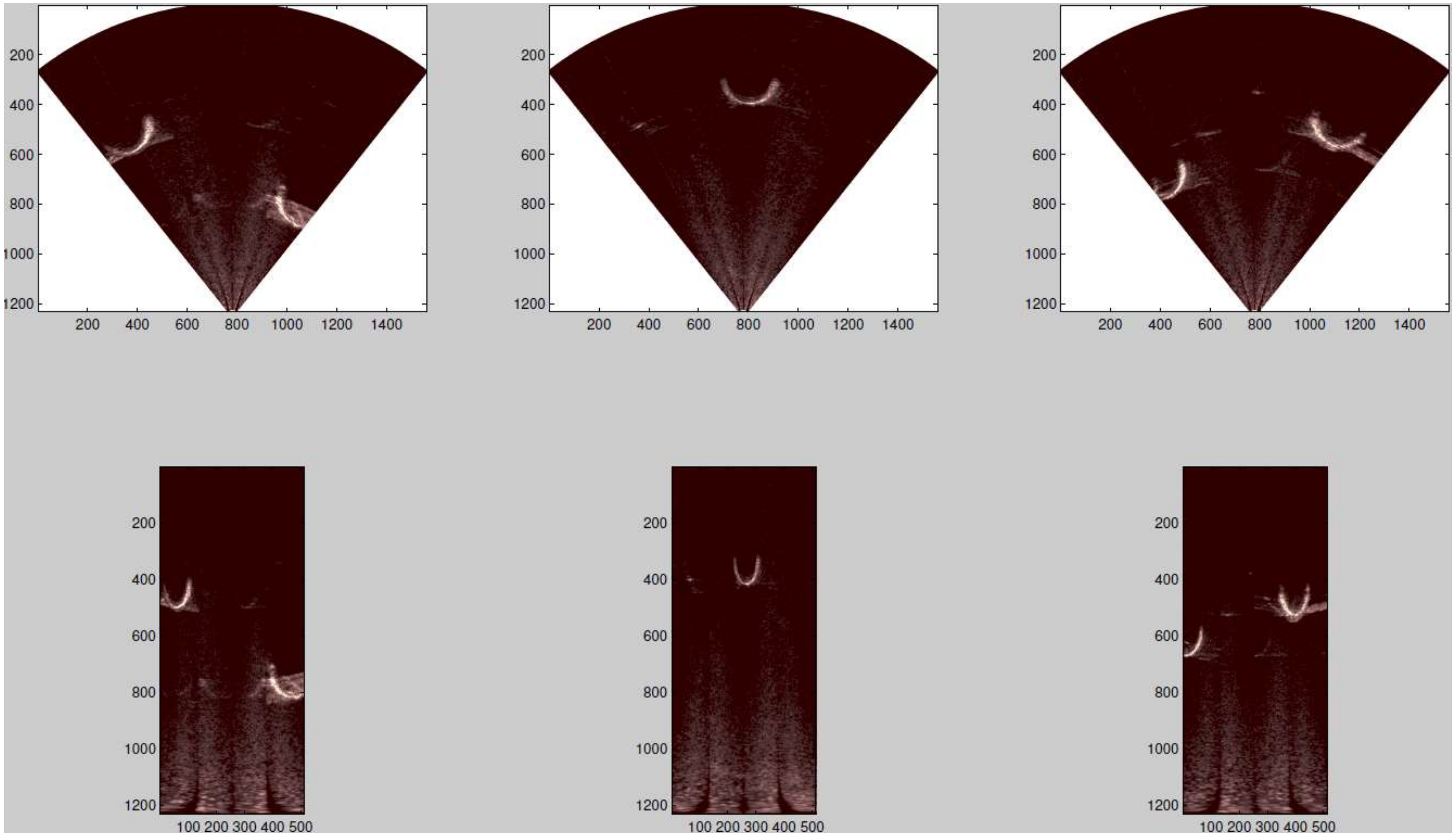
Training



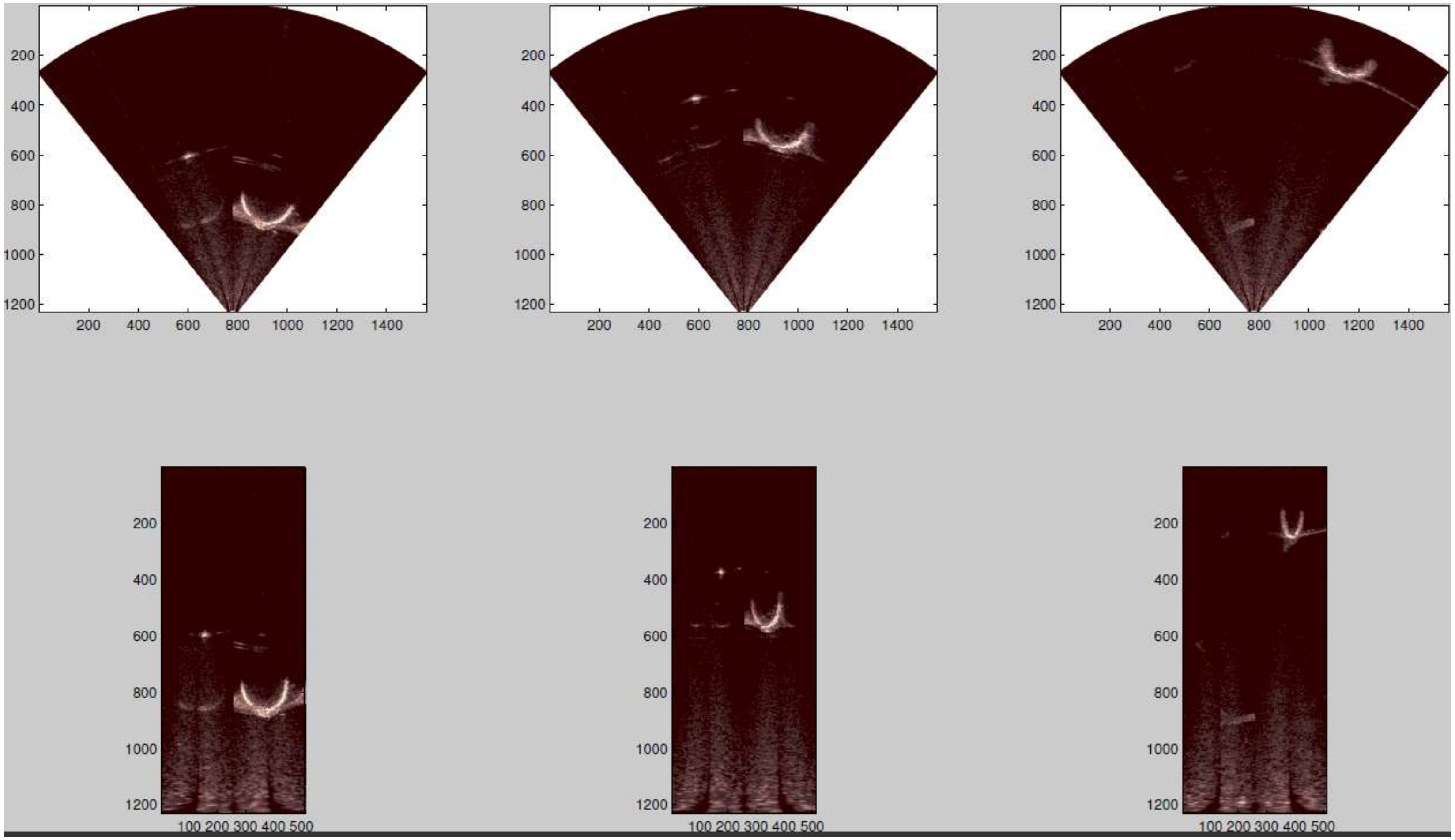
Testing



Sensor Processing – forward looking sonar



Sensor Processing – forward looking sonar



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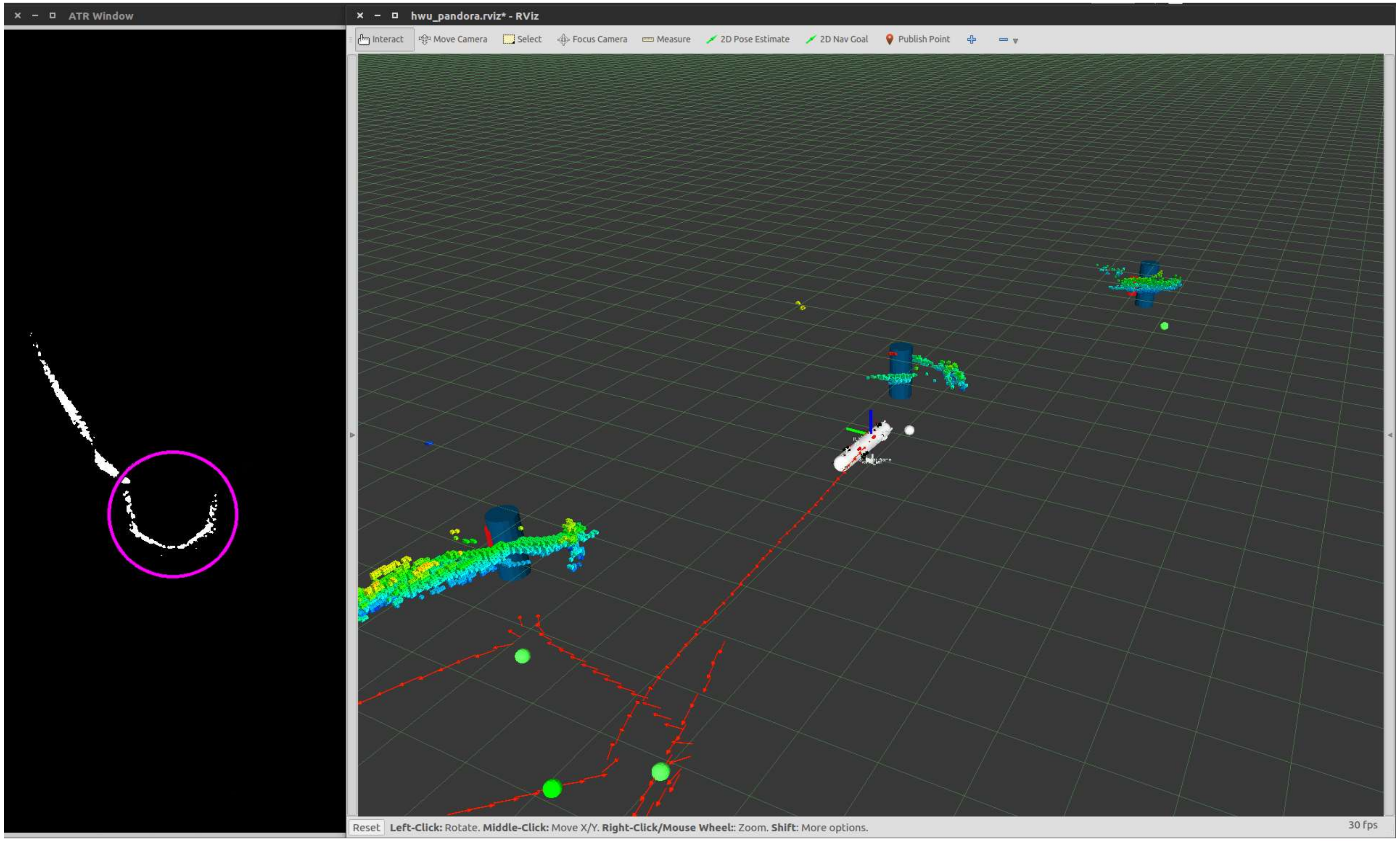
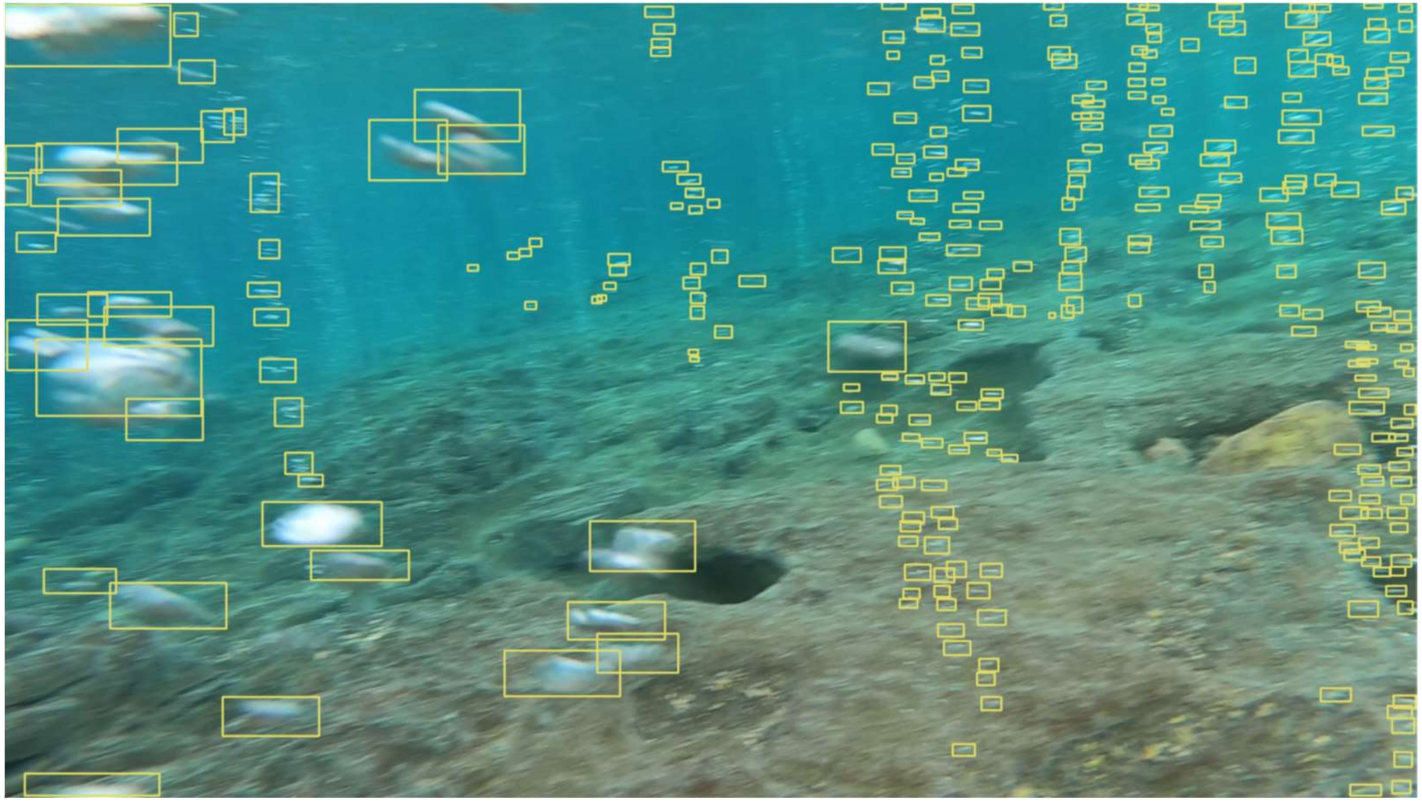
Sensor Processing – forward looking sonar



Sensor Processing – camera

Sensor Processing – camera



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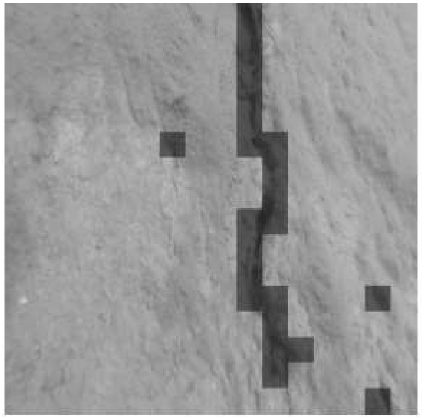
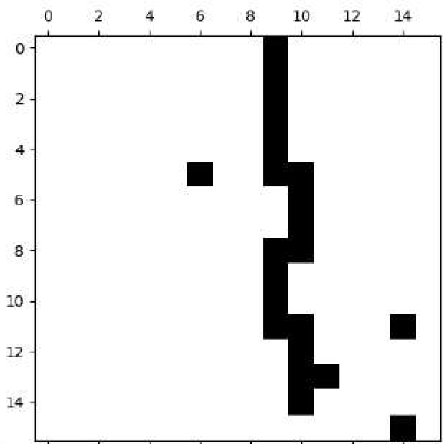
Sensor Processing – camera

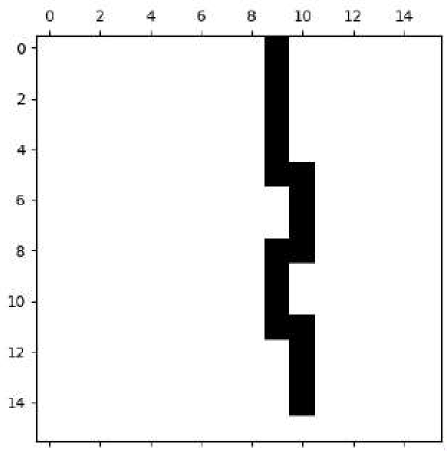
(a) Input Image I^f



(b) Detection Result



(c) $M_B^T(I^f)$

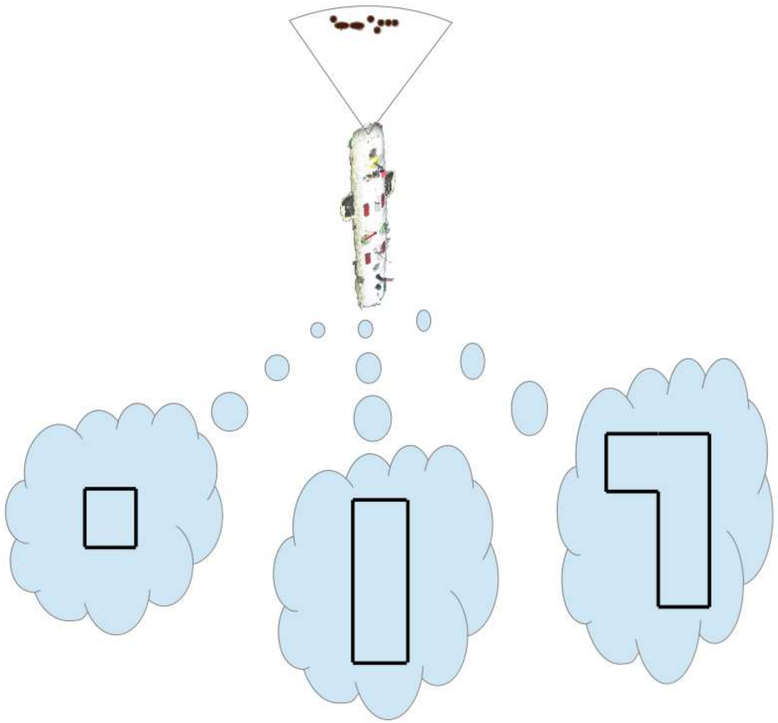


(d) Labeled Test Image

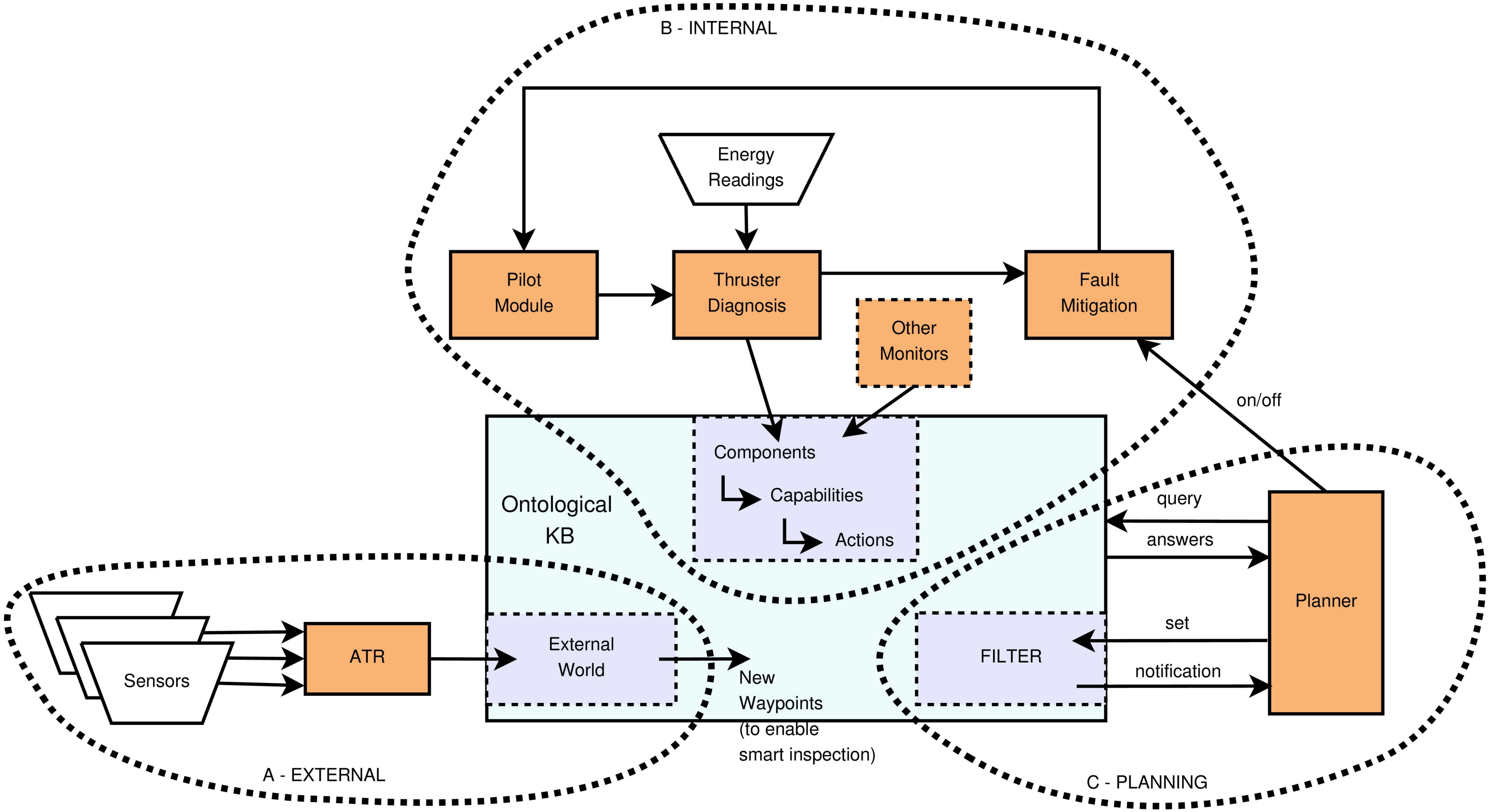
Need for smart inspection

What is the problem?

- Same sensor data leading to **different** possible objects
- **What to do** in order to understand if the sensor data are actually representing Shape A, Shape B Shape C?



Smart inspection in the architecture



Action planning: tree-style trajectory

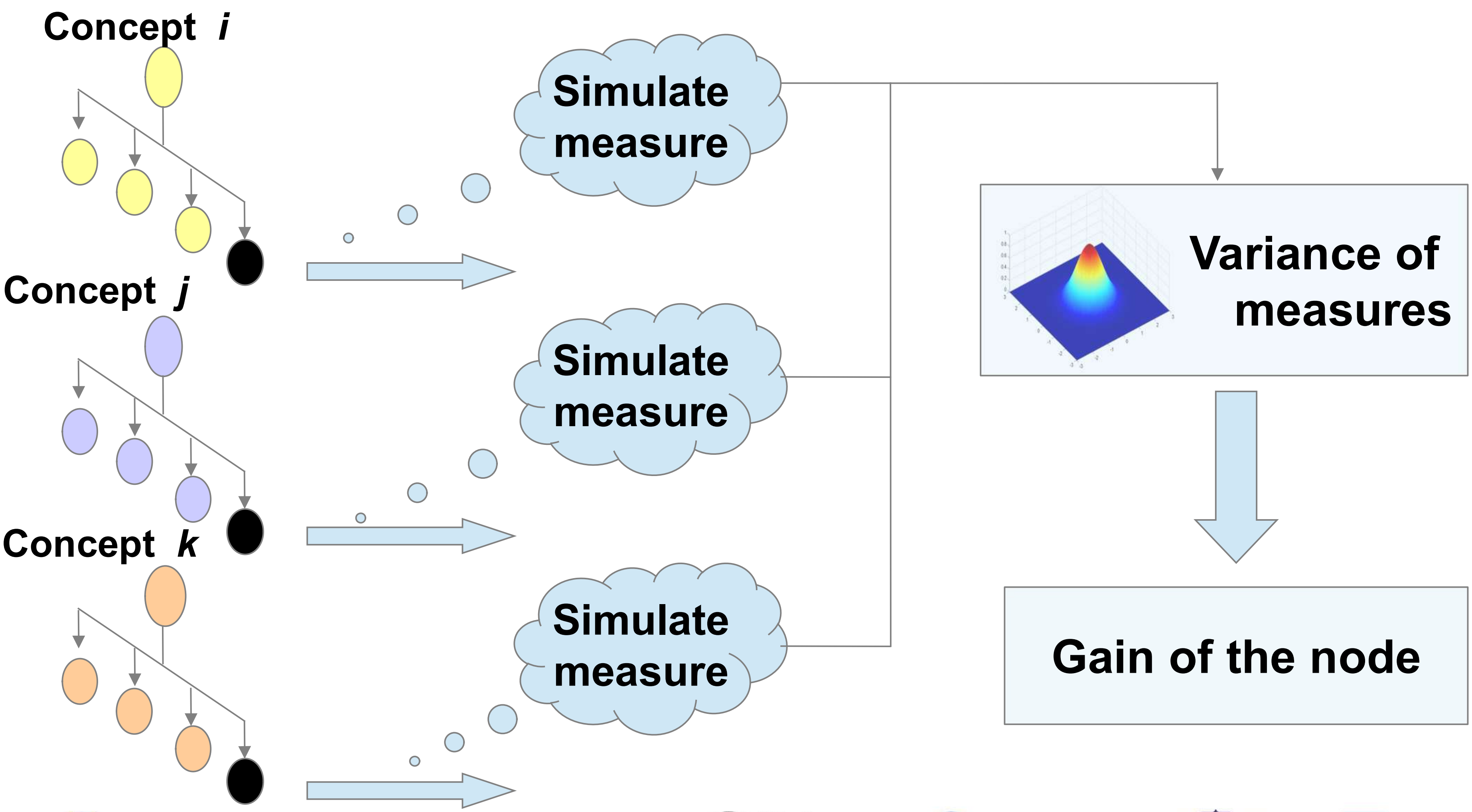
- Build a tree-style trajectory, composed by n basic moves

- For each node, evaluate the **benefits** and the **costs** associated

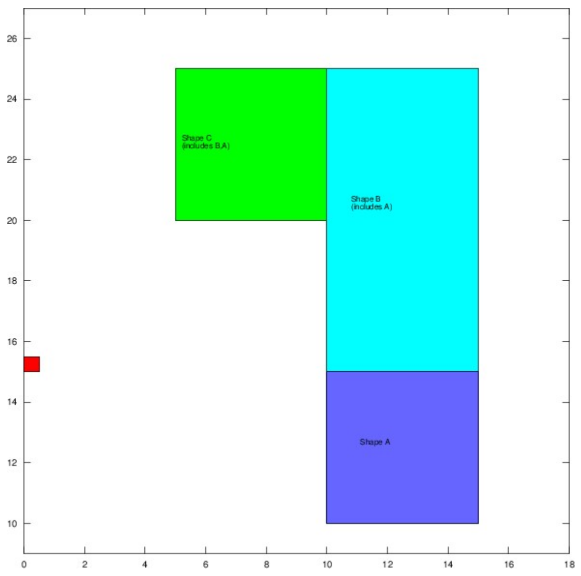
- End with the most effective trajectory [or waypoint] in between a maximum depth

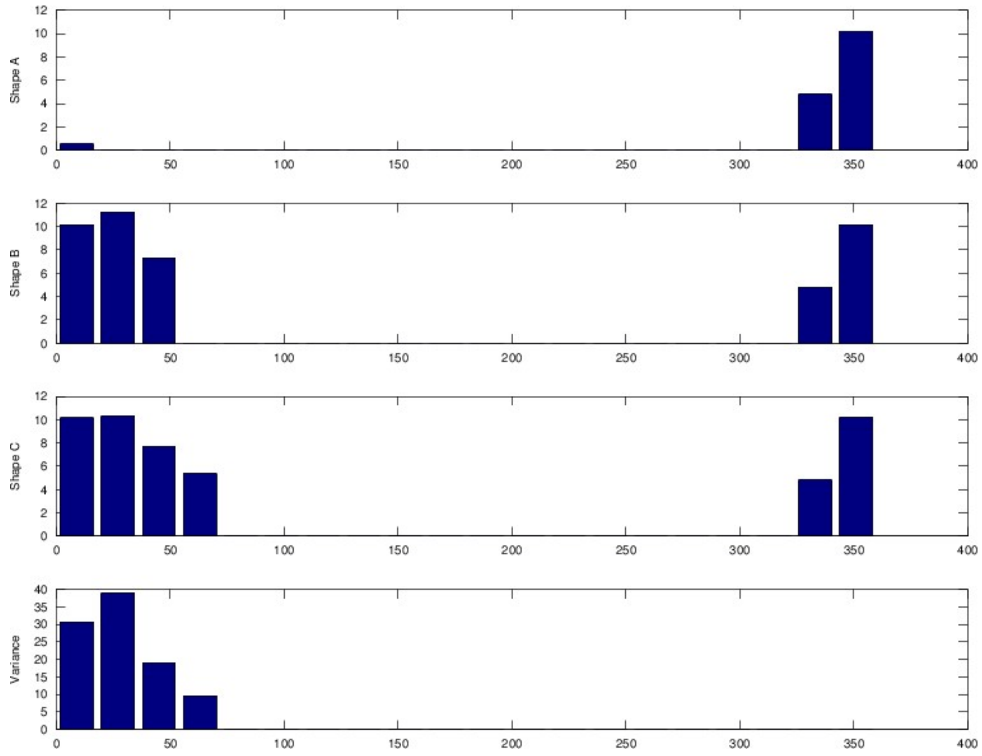
[**On AUV actions to correctly label world information** F. Maurelli, Z. Saigol, D. Lane, M. Cashmore, B. Ridder, D. Magazzeni. *IEEE-MTS Oceans'14*, St. John's, Canada.]

Gain function



Example


Shape C
(includes B,A)
Shape B
(includes A)
Shape A


Shape A
Shape B
Shape C
Variance

Results

- several runs in simulation changing two parameters:

  – **Sonar Range**, from 4m up to 50m

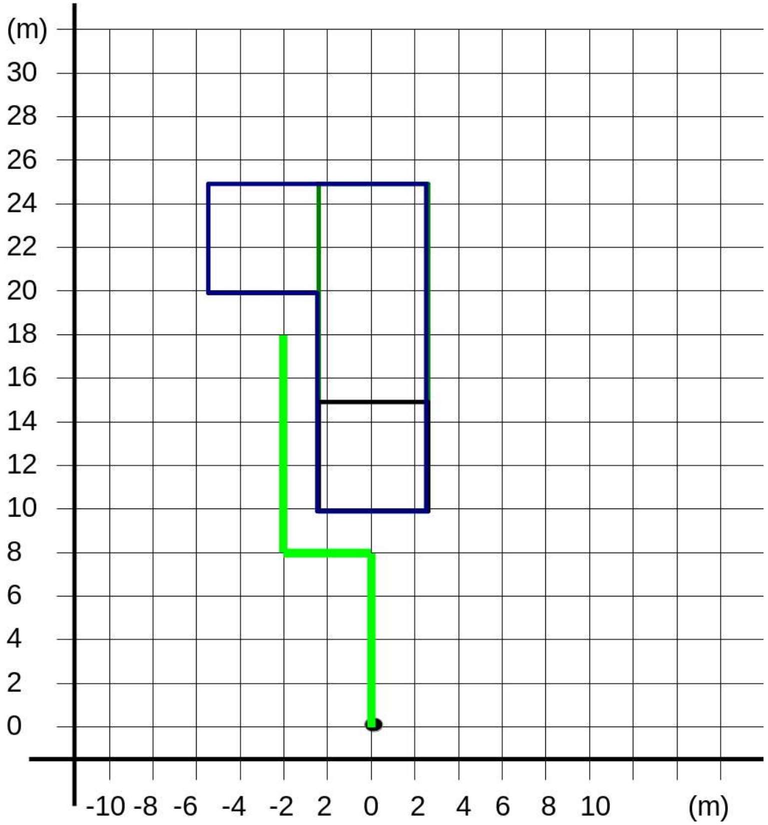
  – **Unit step** for path planning, from 2m up to 12m

- the bigger the range, the shorter the path

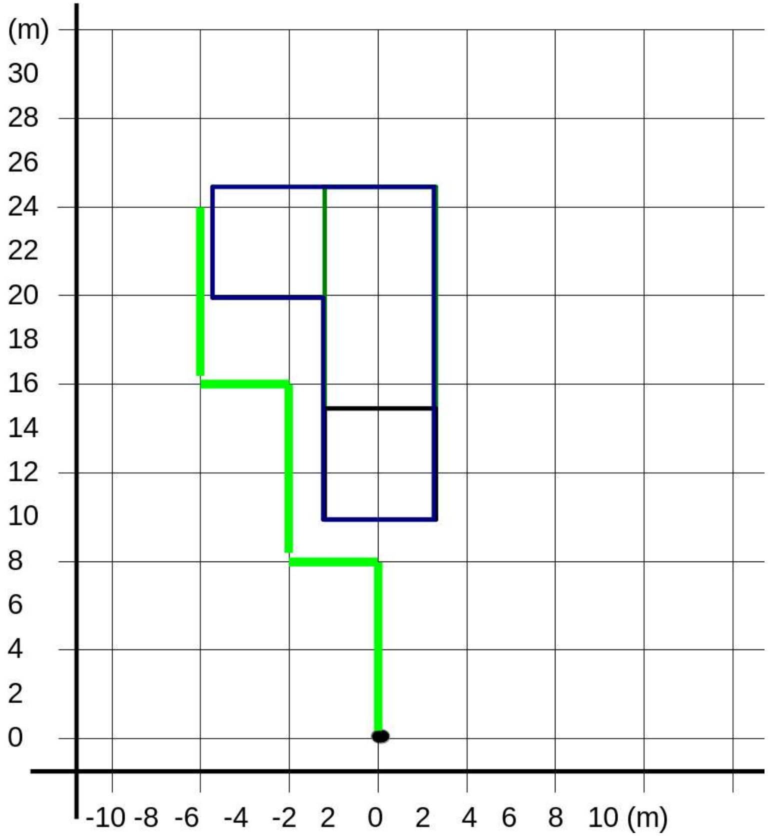
- the bigger the unit step, the shorter the path

  ➢ **Warning**: it needs to be small enough to allow a granular path in complex environments

Results

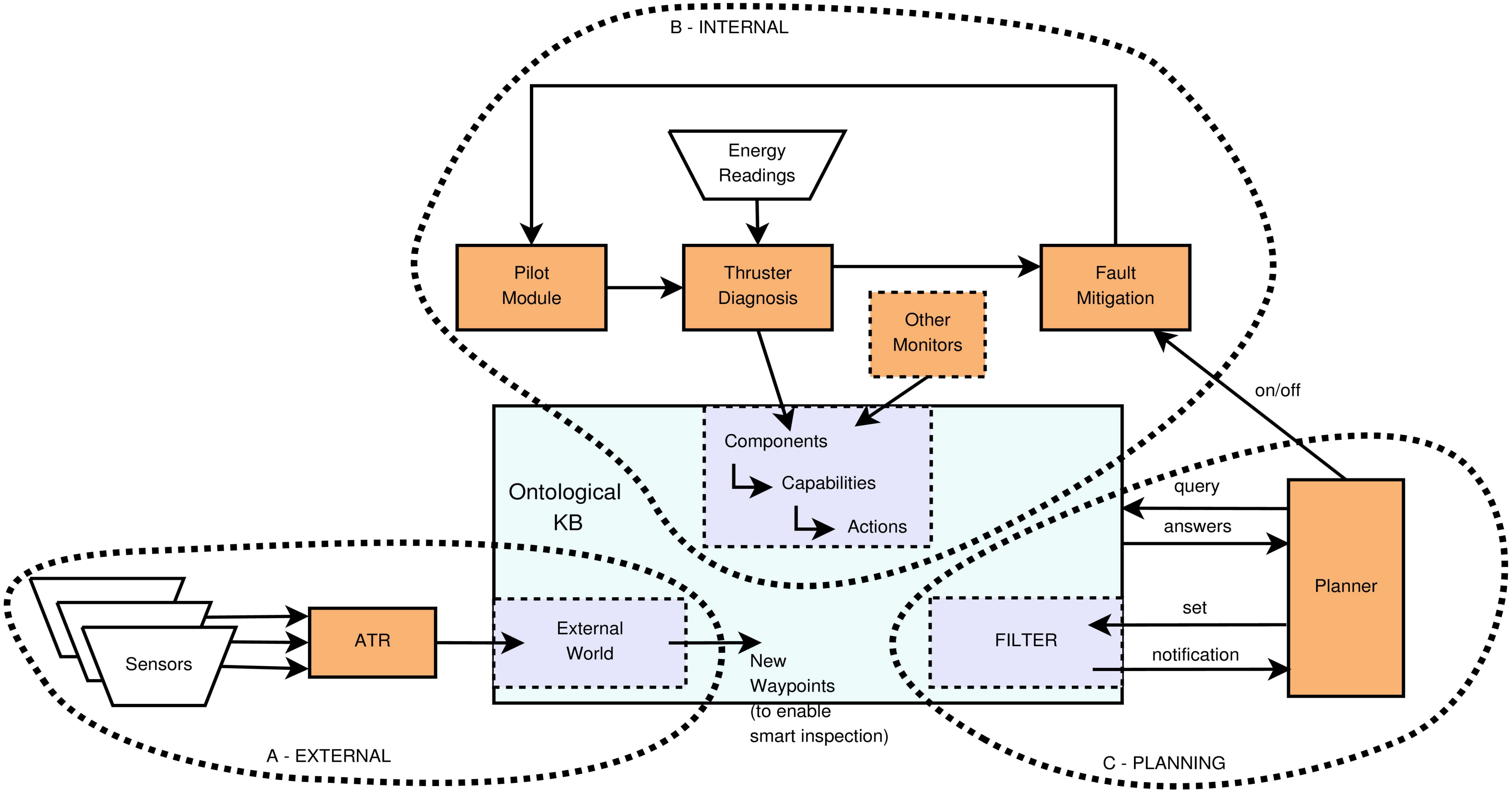


Unit: 2m
Range: 4-16 m

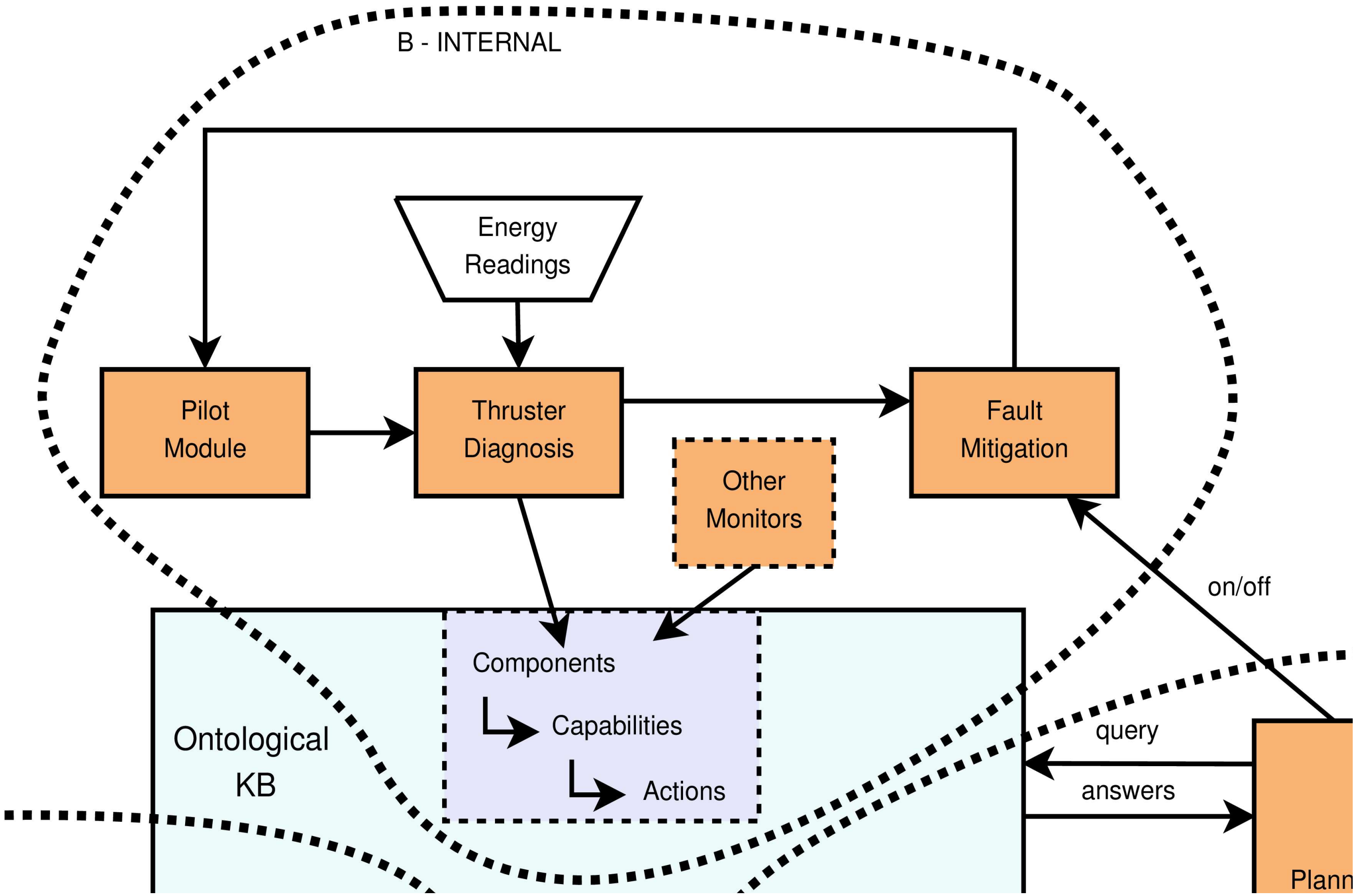


Unit: 4m
Range: 4-16 m

What to do with new waypoints?

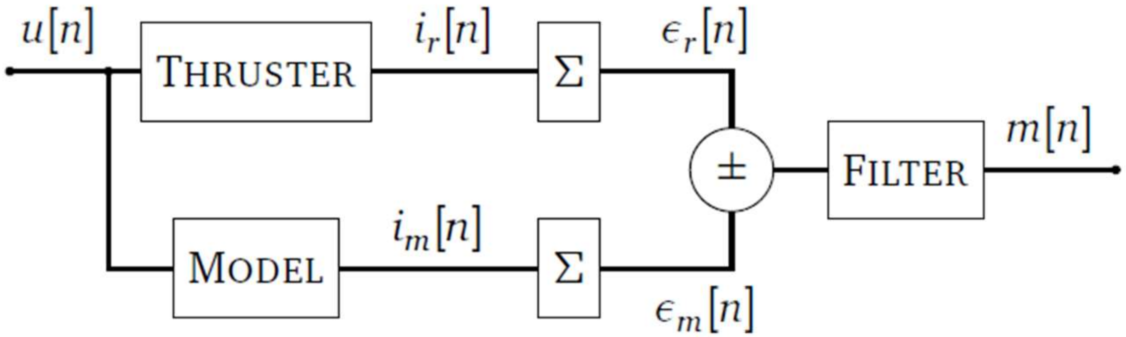


Subsystem B: internal



Thruster Diagnosis

A *model-based* diagnostic method is introduced in Nessie VIII AUV:



Analytically this can be seen as:

$$\epsilon_j[n] = \sum_{n=0}^{W_e} v_{nom}\, i_j[n]\, \Delta_T \qquad j \in \{r, m\}$$

$$m[n] = \sum_{n=0}^{W_f} w_n(\epsilon_r[n] - \epsilon_m[n]) \qquad \sum_{n=0}^{W_f} w_n = 1$$

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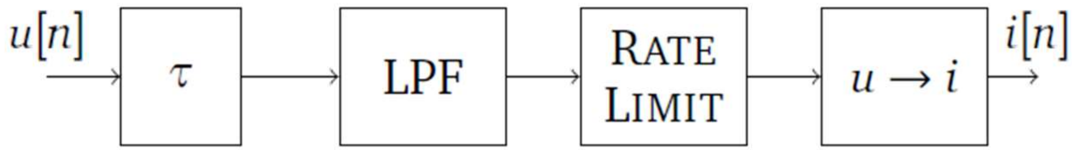
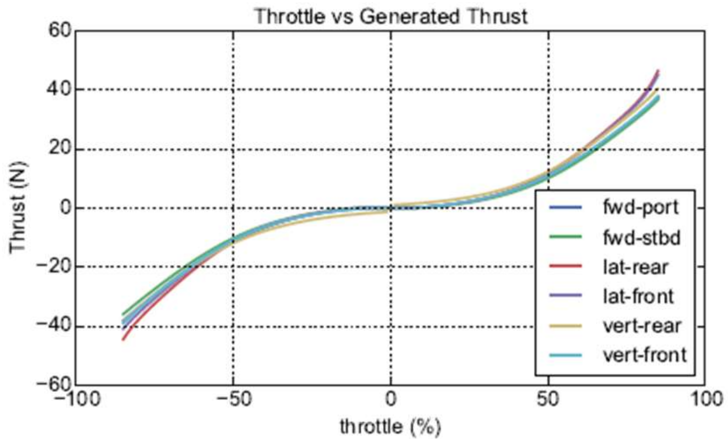
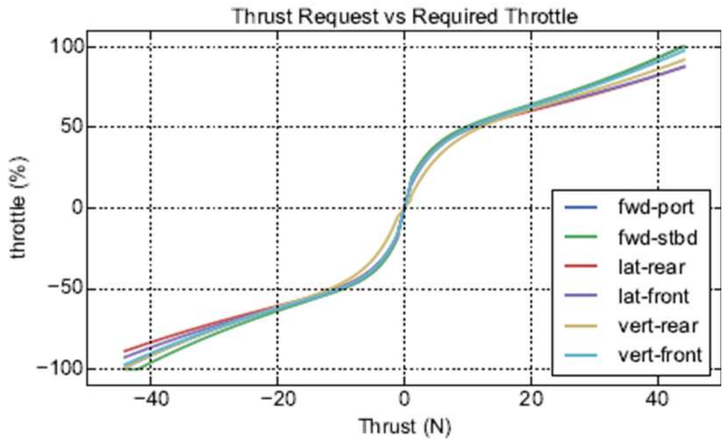
Thruster Model

A *data-driven* approach is used to characterize the six thrusters on Nessie VIII AUV, identifying the *latency* and the *low-pass* of the internal speed controllers together with the *speed to current* characteristics:







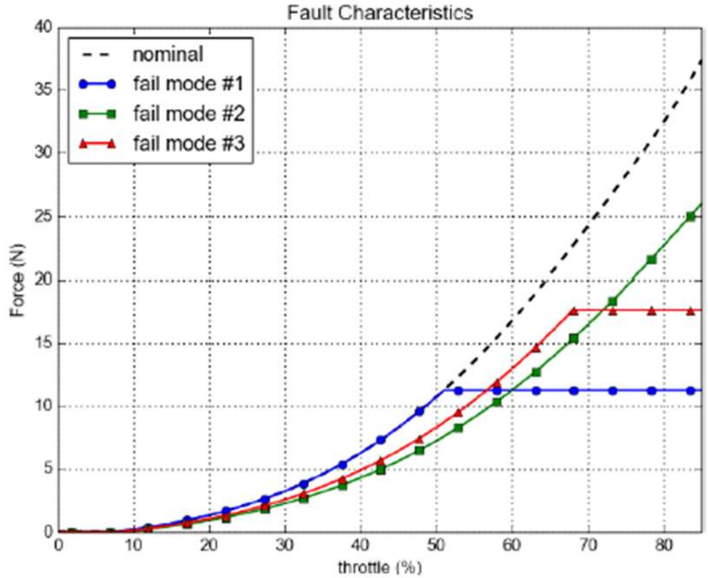
Fault Model

Thrust Efficiency:

$$\eta_T = \frac{T_{real}}{T_{nominal}} \qquad 0 \leq \eta_T \leq 1$$

State updates:

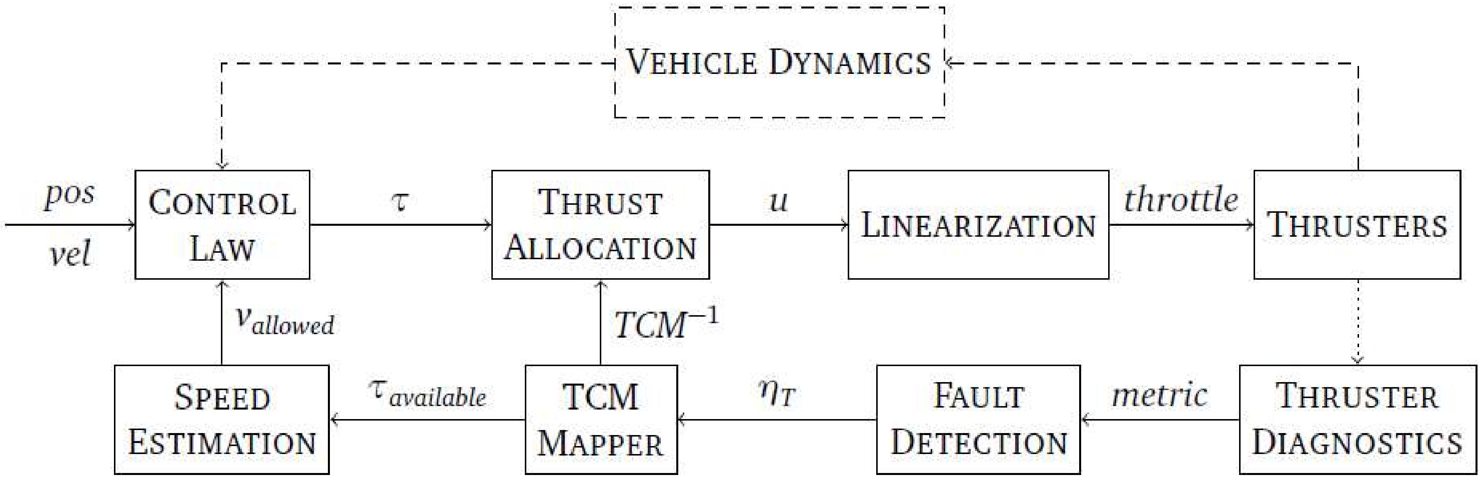
$$\eta_{T_i}[n] = \begin{cases} \eta_{T_i}[n-1] - \Delta\eta_T \\ \eta_{T_i}[n-1] \\ \eta_{T_i}[n-1] + \epsilon\eta_T \end{cases}$$



The proposed architectures uses a *tracking algorithm* to evaluate the state of each actuator thus reacting to the different failure modes.

Fault Mitigation

A new *control schema* is thus implemented in Nessie VIII AUV:



The fault mitigation architecture adjusts at runtime the behaviour of the control software reacting to failures and estimating the available control forces ($\tau_{available}$) and the allowed navigation speed ($\nu_{allowed}$) for each state.

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Allocation

Given the equation of motion:

$$M\dot{v} + C(v)v + D(v)v + g(\eta) = \tau$$
$$\dot{\eta} = J(\eta)v$$

The *force allocation problem* can be written as:

$$f = B^{-1}\tau$$

where B is known as Thruster Configuration Matrix (TCM) and:

$$\tau_{(1\times6)} = [x\ y\ z\ k\ m\ n]$$
$$f_{(1\times N)} = [f_0\ \dots\ f_N]$$

However in presence of faults the inverse of the thruster configuration matrix B can be rewritten as:

$$B_w^{-1} = W^{-1}B^T\left(BW^{-1}B^T\right)^{-1}$$

where W is a weighting matrix:

$$W_{(N\times N)} = \begin{bmatrix} w_0 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & w_N \end{bmatrix}$$

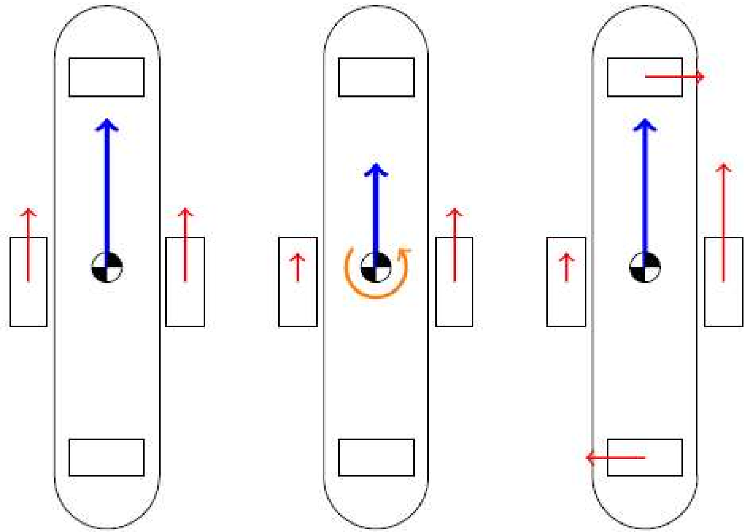
where the coefficients w_i are defined:

$$0 \leq w_i \leq 1 \quad \text{and} \quad w_i = \eta_{T_i}$$

Thrust Remapping

For instance if a degradation is injected in the *port-side forward thruster* of Nessie VIII AUV an additional torque is generated by the unbalanced operation of the two forward actuators.

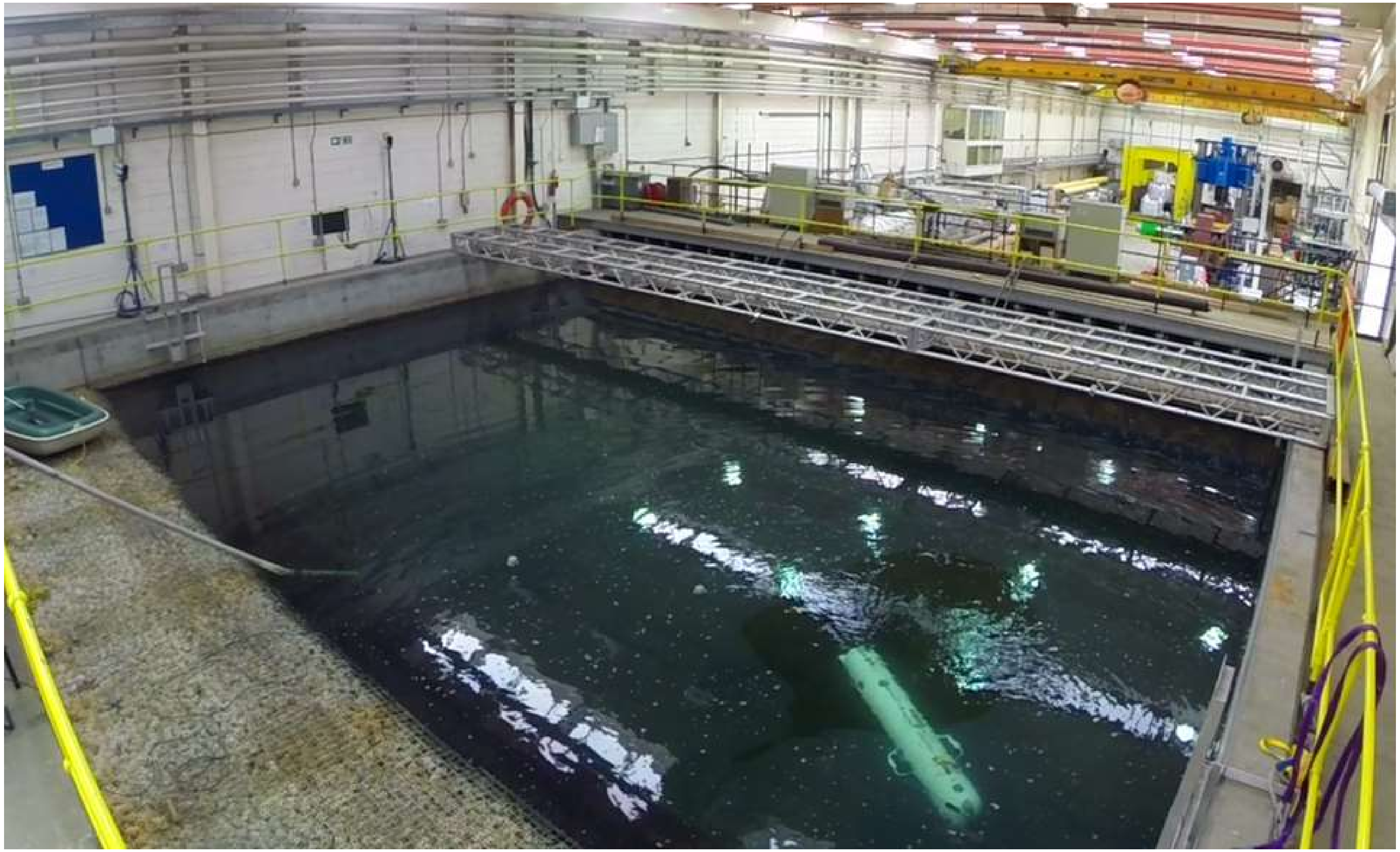
In this case the *mitigation algorithm* remaps the allocation of the *surge* forces among the forward and lateral thrusters rebalancing the distribution of forces.



For instance if we assume $\eta_T = 0.5$ and $\tau = [8\ 0\ 0\ 0\ 0\ 0]$ then without compensation the net force acting on the vehicle fault is $\tau_{eff} = [6\ 0\ 0\ 0\ 0\ 0.37]$. The mitigation algorithm redistributes the forces among the other thrusters so that $f_{remap} = [2.74\ 5.26\ -0.37\ 0.37\ 0\ 0]$ applying the requested control force τ.

[**Energy-aware fault-mitigation architecture for underwater vehicles,** V De Carolis, F Maurelli, KE Brown, DM Lane, Autonomous Robots 41 (5), 1083-1105 - 2017]

Indoor Experiments



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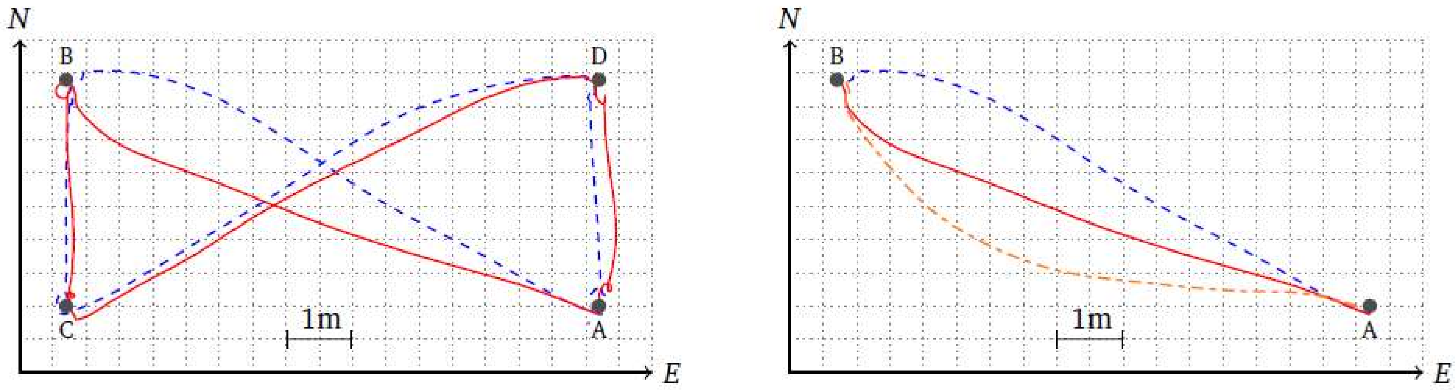
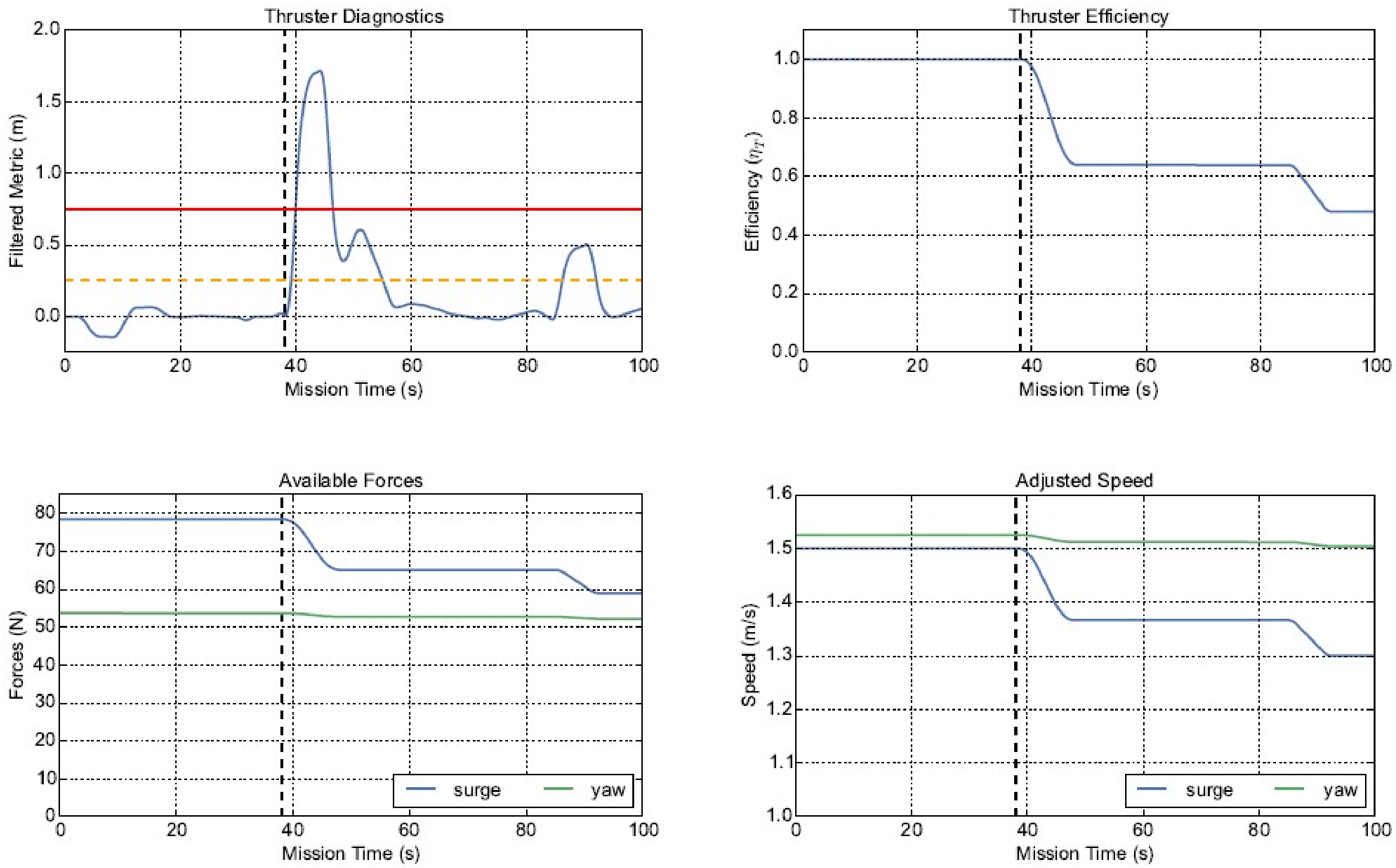
Experimental Results

Trajectory comparison for controlled environment experiments with *forward thruster degradation* faults ($\eta_T = 0.2$). The effect of the mitigation algorithm can be seen in the trajectory leg $\overline{AB}$ where the vehicle adapts to injected fault thus resuming the navigation as originally planned.



On the right is shown the effect of an uncompensated degradation (dotted line) relative to the normal (dashed line) and the mitigated (solid line) trajectories.

Experimental Results



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Forward Thruster Results

Experimental results for inspection task in controlled environment in presence of *port-side forward thruster degradation*. The vehicle completed the inspection task with success for all the different levels of degradation.

η_T	duration (s)	energy (Wh)	rel. dur. (%)	rel. ene. (%)
1.0	126.11	3.60	–	–
0.8	140.99	4.19	11.80	16.30
0.6	148.92	4.62	18.08	28.37
0.4	176.68	5.80	40.09	61.03
0.2	203.77	6.96	61.57	93.11
0.0	204.31	7.02	62.00	94.94

In the case of Nessie VIII AUV we consider as *warning* threshold an increase of 60% and as *critical* one a 100% or a 2-fold increase in the use of *time* and *energy* resources during the execution of tasks.

Lateral Thruster Results

Experimental results for inspection task in controlled environment in presence of *front lateral thruster degradation*. For $\eta_T > 0.6$ vehicle's efficiency is severely reduced and the use of resources is sensibly increased.

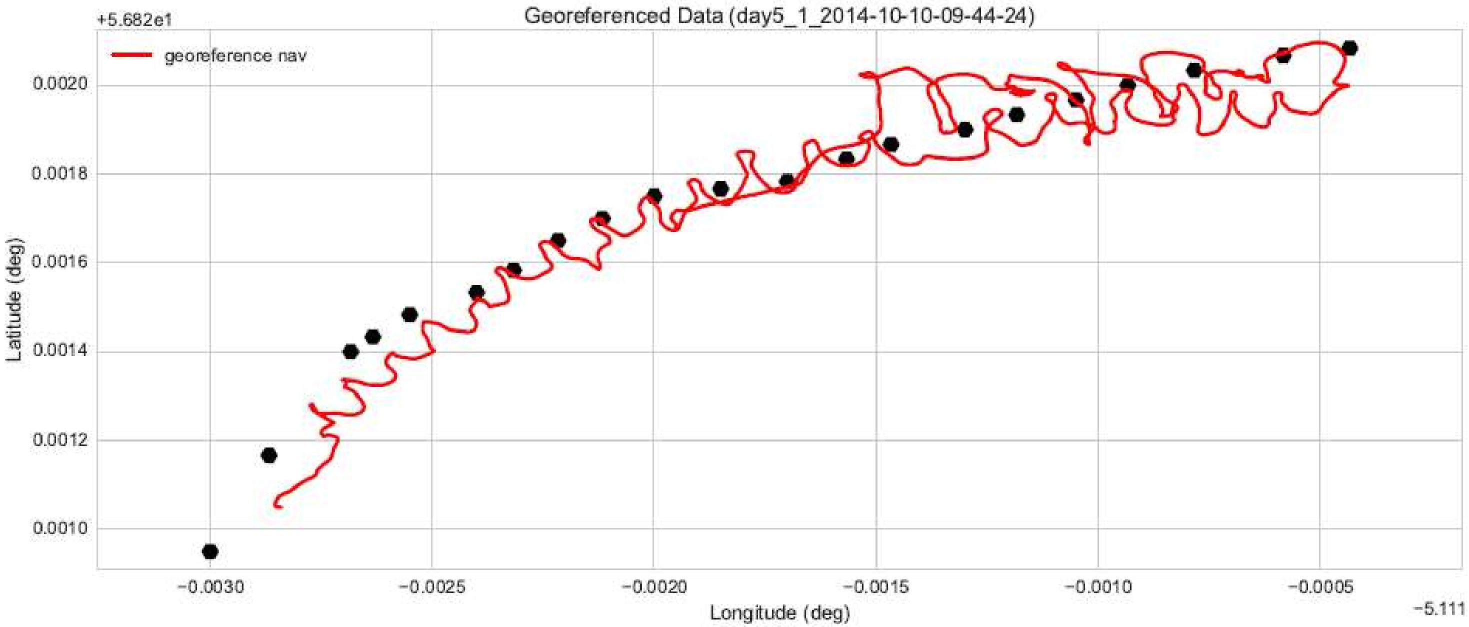
η_T	duration (s)	energy (Wh)	rel. dur. (%)	rel. ene. (%)
1.0	126.11	3.60	–	–
0.8	137.68	4.16	9.18	15.52
0.6	137.30	4.68	8.88	29.87
0.4	197.36	8.03	56.50	123.14
0.2	203.27	8.49	61.18	135.75
0.0	205.95	8.62	63.31	139.37

In the case of Nessie VIII AUV we consider as *warning* threshold an increase of 60% and as *critical* one a 100% or a 2-fold increase in the use of *time* and *energy* resources during the execution of tasks.

Sea Trials Results

Navigation

Nessie AUV conducted 5 days of sea trials in presence of spring tides and moderate currents. The main mission was inspecting the marine pier with the on-board sensors (*forward looking and micro bathymetry sonars, high-res video*) to collect a big dataset for future use.



Energy Performance

In real sea condition inspection tasks are heavily influenced by the effect of tides and the presence of currents. The *energy consumption per unit of distance* is highly influenced by these factors and the navigation style.

Dataset	Duration (s)	Distance (m)	Energy (Wh)	Performance (J/m)
day3-1	2040	246	63.74	934.53
day3-2	608	104	23.42	813.13
day3-3	1156	186	28.09	545.76
day3-4	2417	709	143.77	730.70
day4-1	3432	1258	197.46	565.37
day5-1	2440	736	130.03	636.70
day5-2	890	433	47.15	392.03
day5-3	1513	512	67.07	471.86

Thruster Failure

During field trials Nessie AUV experienced a real failure: the loss of the propeller's blades on the *lateral front* thruster. This has been detected by the *fault mitigation system* together with an injected fault ($\eta_T = 0.4$) on the *starboard-side forward* thruster during some navigation experiments.

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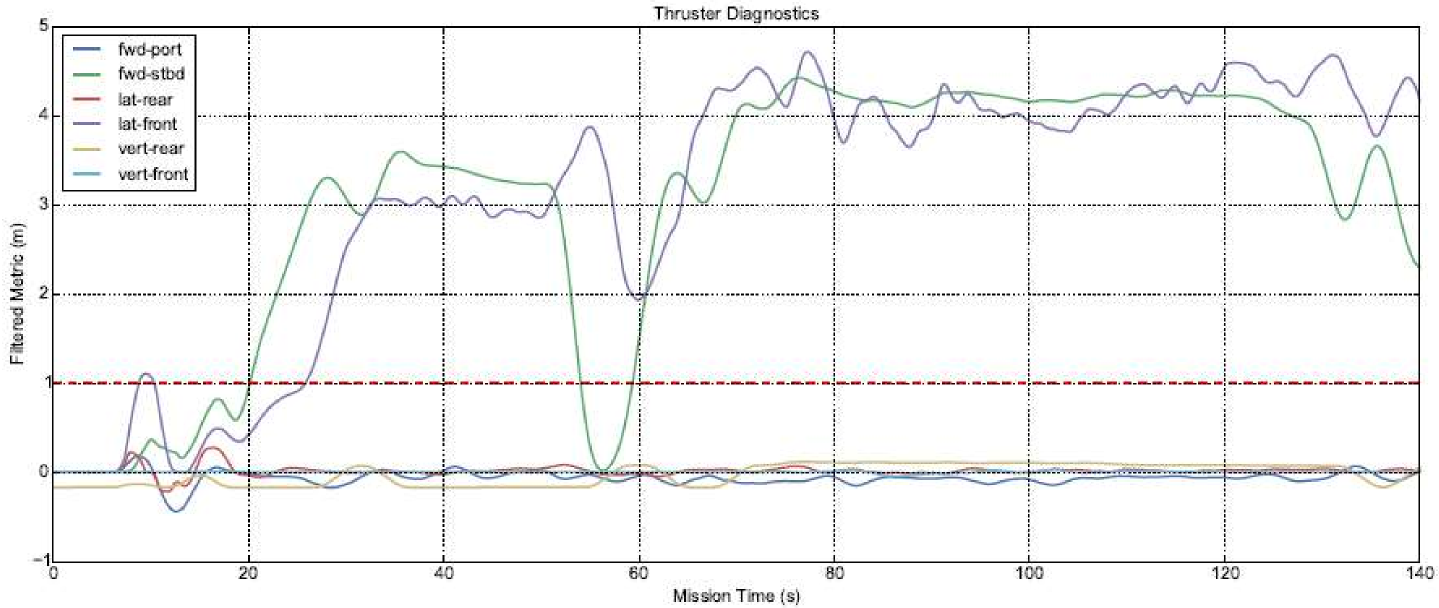

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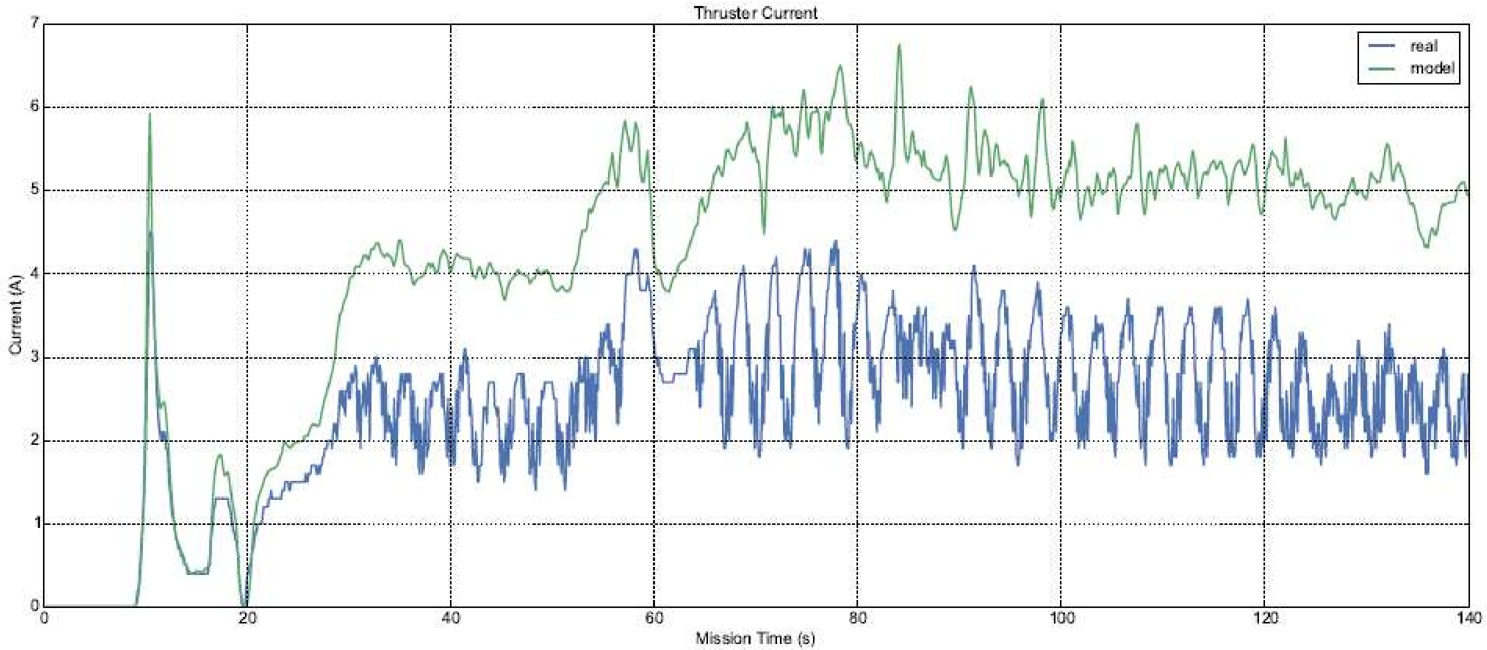

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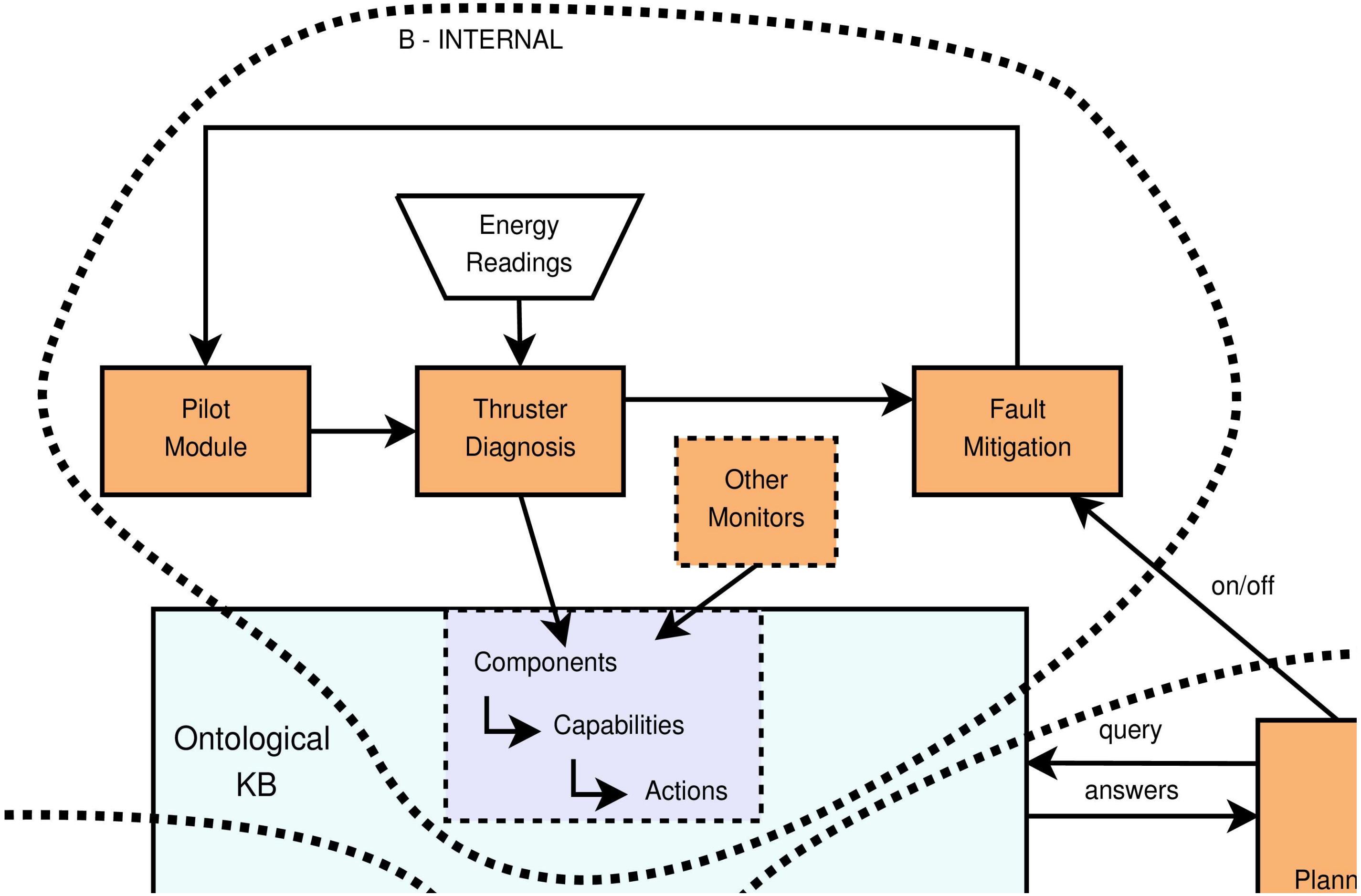
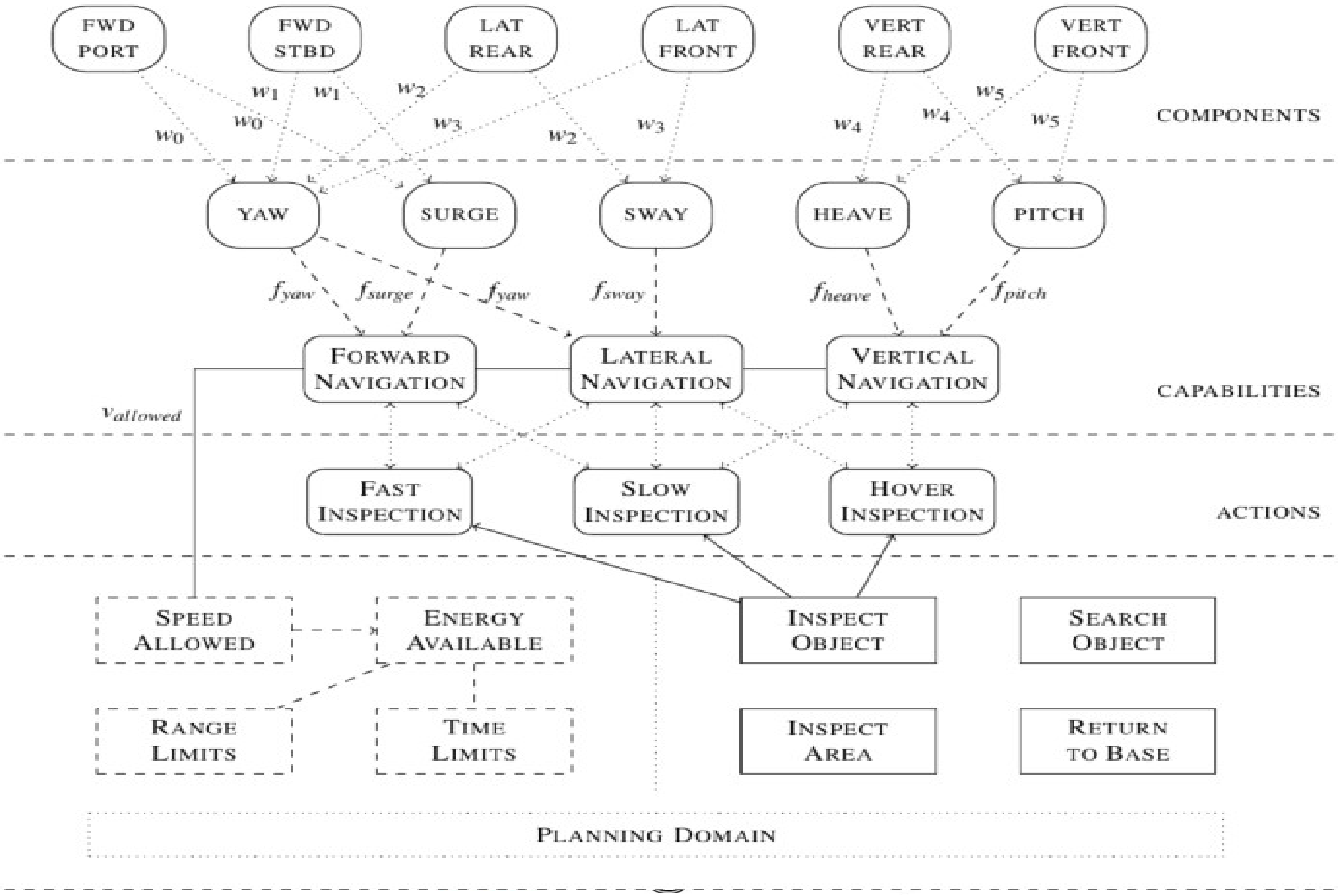
Subsystem B: internal



Subsystem B: internal



Questions ?