PANDORA - Persistent Autonomy Through Learning, Adaptation, Observation and Replanning ⋆

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Abstract: PANDORA is a EU FP7 project that is developing new computational methods to make underwater robots Persistently Autonomous, significantly reducing the frequency of assistance requests. The aim of the project is to extend the range of tasks that can be carried on autonomously and increase their complexity while reducing the need for operator assistances. Dynamic adaptation to the change of conditions is very important while addressing autonomy in the real world and not just in well-known situation. The key of Pandora is the ability to recognise failure and respond to it, at all levels of abstraction. Under the guidance of major industrial players, validation tasks of inspection, cleaning and valve turning have been trialled with partners' AUVs in Scotland and Spain.

1. INTRODUCTION

Whilst humans and animals perform effortlessly doing complicated tasks in unknown environments, our human-built robots are not very good at being similarly independent. Operating in real environments, they easily get stuck, often ask for help, and generally succeed only when attempting simple tasks in well-known situations. We want autonomous robots to be much better at being autonomous for a long time (persistent autonomy), and to be able to carry out more complicated tasks without getting stuck, lost or confused. Following the Deep Water Horizon disaster in the BP Macondo oilfield in the Gulf of Mexico in 2010, Oil Companies are developing improved ways to cost effectively and safely carry out more frequent inspection, repair and maintenance tasks on their subsea infrastructure. This is particularly challenging in deep water. To date, Autonomous Underwater Vehicles (AUVs) have been deployed very successfully for various forms of seabed and water column transit survey. First commercial units will soon be applied to simple hovering inspection tasks, with future units expected to address much harder intervention where contact is made to turn a valve or replace a component. Because these vehicles reduce or remove the need for expensive ships, their adoption is expected to grow over the next 5 to 10 years.

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To be successful commercially, these hovering AUVs must operate for extended periods (12-48 hours +) without the continual presence of a surface vessel. They must therefore demonstrate persistent autonomy in a challenging environment. We therefore choose this application focus to evaluate the projects research, with guidance from BP, Subsea7 and SeeByte Ltd. on the project's Industrial Advisory Group. Three essential areas have been identified:

- Describing the World
- Directing and Adapting Intentions
- Acting Robustly

We believe that they are core research areas in which significant advancements is pivotal for Persistent Autonomy. This paper is structured as follow: section II briefly describes the system architecture and the relations between different core fields; section III presents the scientific areas addressed by the Pandora project; section IV presents the three scenario tasks with a brief presentation of in-water trials; section V outlines the conclusions.

2. ARCHITECTURE

Figure 1 outlines the computational architecture designed for development and study of persistent autonomy. Key is the notion that the robot's response to change and the unexpected takes place at one or a number of hierarchical levels. One of the main features in the PANDORA architecture is the separation of the software components needed for an autonomous vehicle mission into multiple

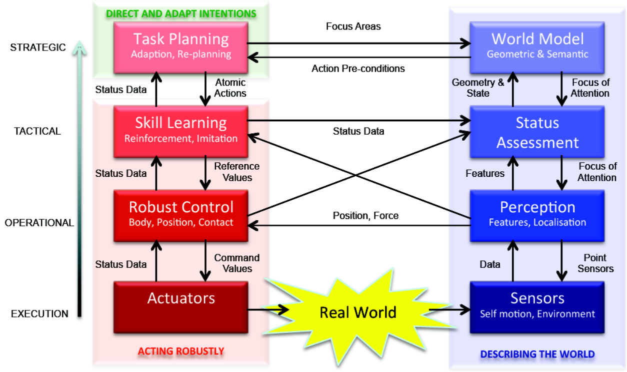

Fig. 1. PANDORA: Computational architecture to develop and study persistent autonomy

logical layers, each of them responsible for a specific aspect of its final behaviour. In order to describe this architecture two logical separations can be made. The first one discriminates components on the basis of their level of abstraction from the physical representation of the vehicle. The second one is based on the role that each component has in the mission's OODA loop (Observe, Orient, Decide and Act), in terms of producing effects on the external world (*acting*), extracting a representation of it (*observing*) or setting the goals for the behaviour of the platform itself (*deciding*). In the vertical hierarchy the *execution*, *operational*, *tactical* and *strategic* layers can be found. The *execution* layer, at the bottom of the hierarchy, interacts directly with *sensors* and *actuators*, exchanging feedback data and commands with the upper layers. The *operational* layer, instead, supervises different actuators, fusing data and extracting features from multiple sensors. The *tactical* layer supervises the lower layers keeping track of the vehicle status and adapting the platform behaviour at task level. Finally the *strategic* layer sits on top of this hierarchy and is responsible for high-level decisions, adapting the overall mission, selecting focus areas and setting the goals for next tasks. In the second separation three main areas can be found. The first comprises the components responsible for *describing the world*, thus representing the internal and external beliefs of the vehicle, its perception and its internal status. The second is in charge of *acting robustly*, thus including the low-level control schemes and the learning subsystems. The third includes the components which *direct and adapt intentions* of the platform during the execution of a mission.

3. SCIENTIFIC AREAS

3.1 Describing the World

Understanding the surrounding world is essential for a high level of autonomy, feeding information into the planning and control systems. In the PANDORA framework, ontologies are used as a way for the robot to organise the knowledge about the world, not just in geometric concepts, but attaching a semantic label. This opens the possibility to reason on the ontology, expand the knowledge, and use this knowledge to make decisions, having a symbolic abstract representation which can be used by the planning system. An example of an ontology in the underwater domain is in Figure 2. It shows relations among classes (yellow circles) and individual of specific classes (blue diamonds). Note that in this example there are three instances of the class *Circle* and two instances of the class *RoundPillar*. This is due to the probabilistic approach taken in consideration when building the knowledge base. Partial information about basic shapes may or may not lead to a more complex structure, depending on future views and actions from the AUVs. More detailed work discussing the need to consider uncertainty can be found in Maurelli et al. [2013] and Maurelli et al. [2014b]. A strategy to correctly label world information, linking the planning system to the classification module can be found in Maurelli et al. [2014a].

3.2 Directing and Adapting Intentions

Predefined plans are commonly used for AUV mis- sions. However, when acting in uncertain and unknown underwater environments, with processes and other agents changing the world in unpredictable ways, and with notoriously imprecise and noisy sensors, plans can fail for several reasons. The work carried out aimed to provide online planning and replanning capabilities. Three possible reasons for replanning were considered:

- action failure: an action execution reports failure, using the ROS action feedback;
- change of environment: there is a change in the environment that invalidates the plan, or new information pertinent to mission goals; or
- budget difference: the difference in estimated cost (time or energy usage) differs from that of real execution, and the executor calculates that the plan is invalidated (the real cost was high) or that there is room to perform extra tasks (the real cost was low).

The planning system represents the brain and the bridge among the knowledge base fed by sensor data analysis and reasoning, and the control of the vehicle, which interact with the environment. More detailed work on AUV Mission Control via Temporal Planning can be found in Cashmore et al. [2014] and Cashmore et al. [2013].

3.3 Skill Learning for Persistent Autonomy

The tasks AUVs need to undertake and successfully complete can benefit from applying machine learning algorithms to increase the AUV adaptability. In order to program intervention tasks in a flexible and intuitive way the Pandora project has investigated the use of a machine learning algorithm known as LbD. Rather than analytically decomposing the problem and manually programming a desired behaviour, the LbD infers the knowledge from a set of user demonstrations. This kind of algorithms follow three sequential phases: *Demonstration* where a batch of task examples performed by a human pilot are recorded; *Learning*, where a model is created by generalizing all the demonstrations; and *Reproduction*, where the model is used to accomplish new instantiations of the learned task. Using such a technique, the framework becomes easily extensible and any intervention tasks (involving both the AUV and manipulator motions) can be added effortlessly just from operator demonstrations. Fig. 3 shows the demonstration phase of the proposed

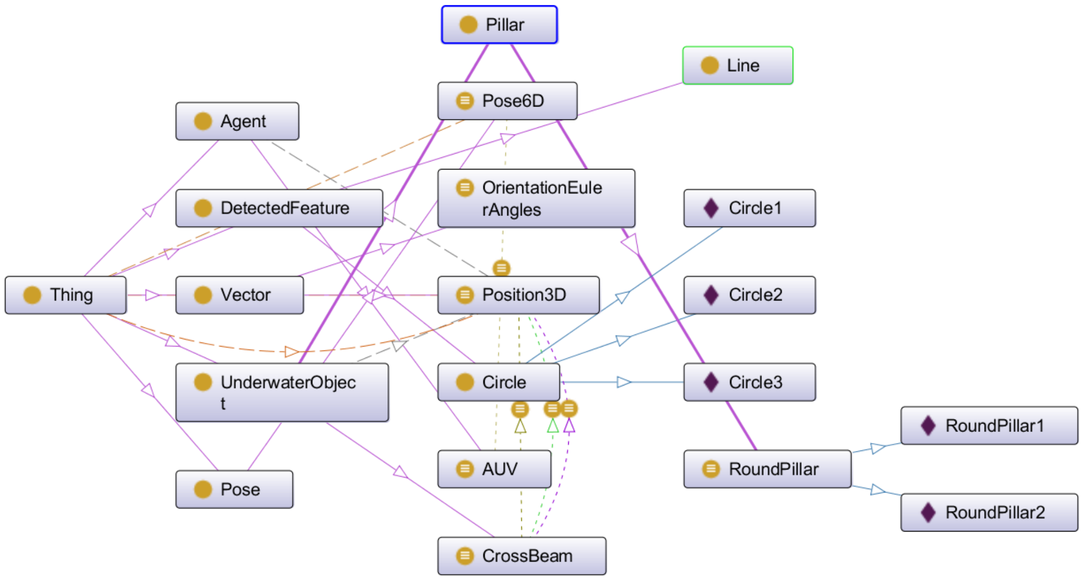

Fig. 2. The OWL file built representing a portion of the vehicle knowledge. Blue diamond are the instances of classes (yellow circles). As it is possible to see, there are three instances of *Circle*, but only two instances of *RoundPillar*. This is normal, because not all the detected circles are then associated with the concept *RoundPillar*.

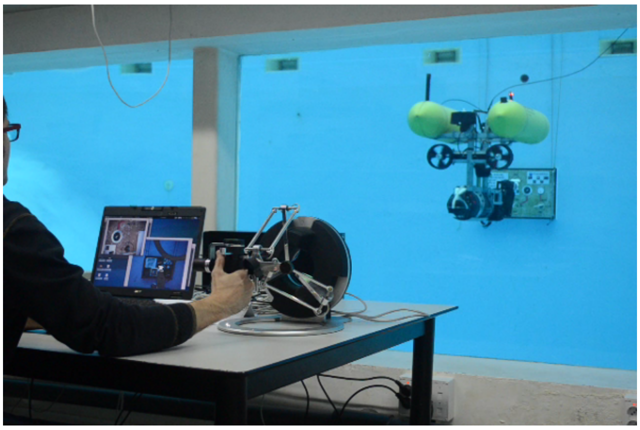

Fig. 3. A user performing a demonstration using the Omega 7 haptic device and the GUI for the Girona 500 AUV

approach. More detailed work on machine learning approaches for AUVs can be found in Jamali et al. [2015] and in Ahmadzadeh et al. [2014].

3.4 Robust Control Strategies for Efficient Positioning and Interaction

The motion control problem for autonomous underwater vehicles has been an active research field for the past two decades and continues to pose considerable challenges to control designers especially when the vehicles are affected by severe environmental disturbances and exhibit large model uncertainties. The particular case of the vehicles used in this work (Girona500 and Nessie) is a clear example of vehicles that target complex operations and, in the case of Girona500, dexterous tasks (i.e. manipulation of underwater equipment such as control valves) while it might be subject to the influence of strong external disturbances caused from ocean currents and waves. Fig. 4 shows the velocity and pose control schemes adopted in this project, along with the thruster allocation module that maps the controllers output into thruster commands. This figure shows how the proposed low-level control system can equally deal with pose, velocity or force requests. More detailed work on AUV control can be found in Karras et al. [2013].

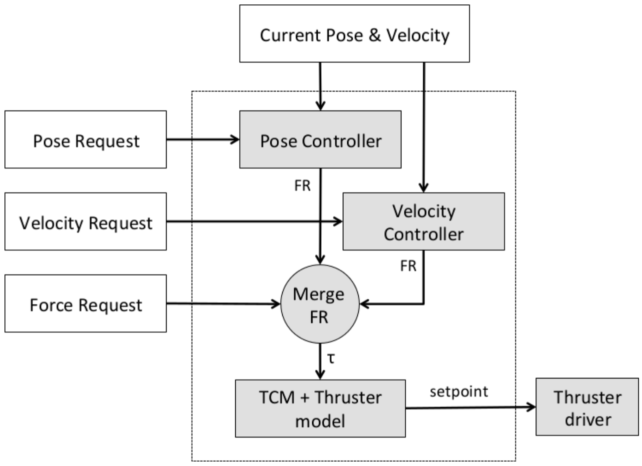

Fig. 4. Girona 500 I-AUV control scheme.

4. TEST SCENARIOS

The Pandora project aims to demonstrate the progress in the above mentioned research areas through the execution of the following three tasks:

- Autonomous inspection of an underwater structure
- Autonomous location, cleaning and inspection of an anchor chain
- Autonomous grasping and turning of a valve from a swimming, undocked vehicle

The following sections will briefly describe how these goals were achieved.

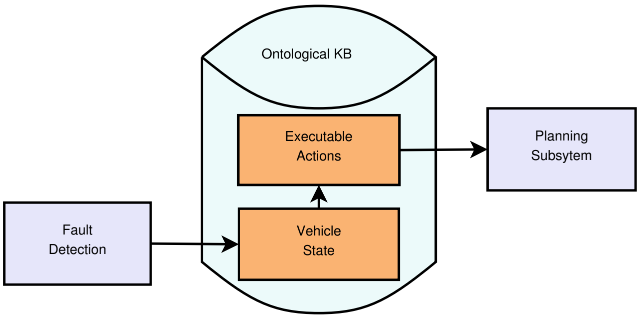

Fig. 5. The role of the Knowledge Base among the planning system and the faults that can happen during the mission.

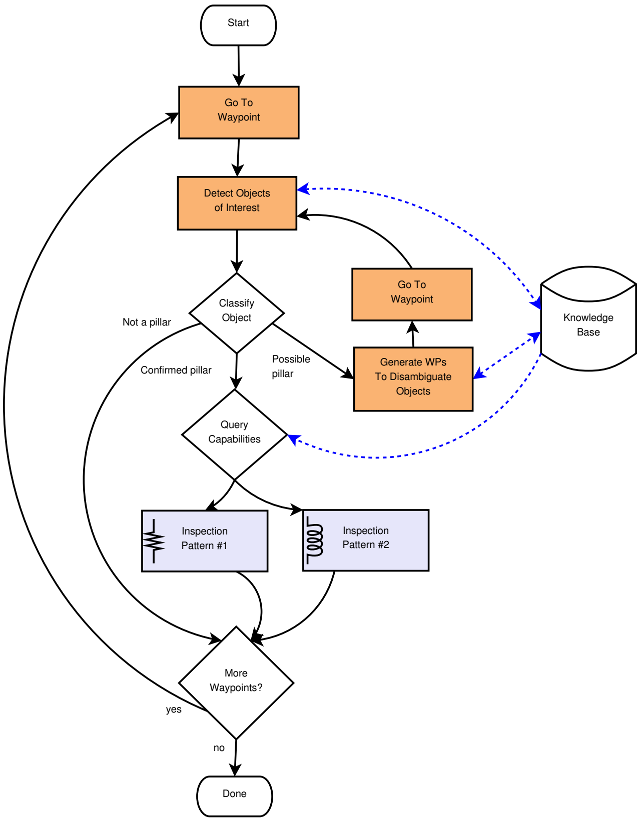

Fig. 6. Model of the planning system performing an inspection task, in relation to new items discovered and faults.

4.1 Task A: Autonomous inspection of an underwater structure

In the inspection scenario, a key area of work is the interaction among the knowledge base, fed by sensor data processing, and the planning system. A particular emphasis is given to the ability to recover from faults in order to continue the inspection. Fig. 5 shows the relation among action capabilities and the planning system. In particular, a diagnostic module has been developed in order to detect a thruster failure, with a link among the degrees of freedom of the vehicle and the executable actions. The vehicle's behaviour in the inspection task is described in Fig. 6.

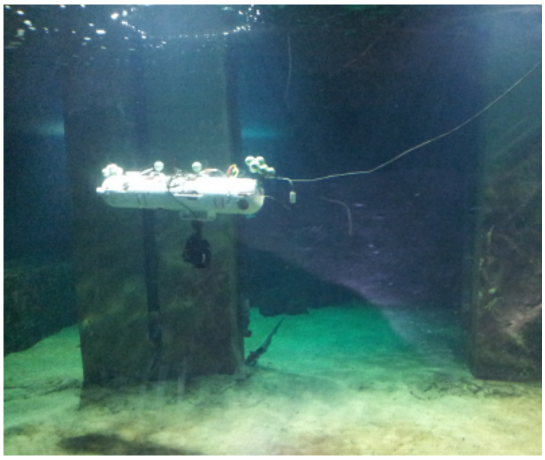

Fig. 7. $Nessie^{AUV}$ in the Ocean Frontier, at The Underwater Centre in Fort William (Scotland).

First preliminary tests happened with the vehicle Nessie AUV at Ocean Frontier, The Underwater Centre, Fort William, and in the wave tank of Heriot-Watt University 7.

Fig. 8 shows the RViz representation of the trajectory of the inspection task. The vehicle is initially given three inspection points, with probable locations of three pillars that need to be inspected. The knowledge-driven actions allows the vehicle to have multiple views of the potential target from different viewpoints before engaging the inspection action at the first point. Moving then to the second point, the multiple-view classification tells the vehicle that the potential target is not of interest, therefore moving to the third and final point. When engaging the close inspection of the pillar moving laterally, pointing all sensors to the target, an injected lateral thruster failure is triggered. Through the results of the diagnostic system and the information in the knowledge base, the vehicle realises that its current action cannot be executed anymore, and therefore decides to switch inspection pattern, in order to complete the high-level goal at its best.

4.2 Task B: Autonomous location, cleaning and inspection of an anchor chain

Maintenance of underwater chains is a costly but necessary need for off-shore applications.

In performing this task, the Girona 500 AUV is equipped with a forward-looking imaging sonar and a high-pressure water jet. Its goal is to locate the correct anchor chain and traverse it to remove the marine growth using the water jet. Thereafter it revisits the chain and brings back complete inspection data for subsequent post processing. Fig. 11 shows the different steps in the execution of the task. The work was tested in the CIRS tank (Fig. 10), with the vehicle successfully able to follow the chain and to produce a accurate sonar mosaic of the environment (Fig. 9). More information about the chain cleaning task can be found in Hurtos et al. [2013] and in Hurtos et al. [2014].

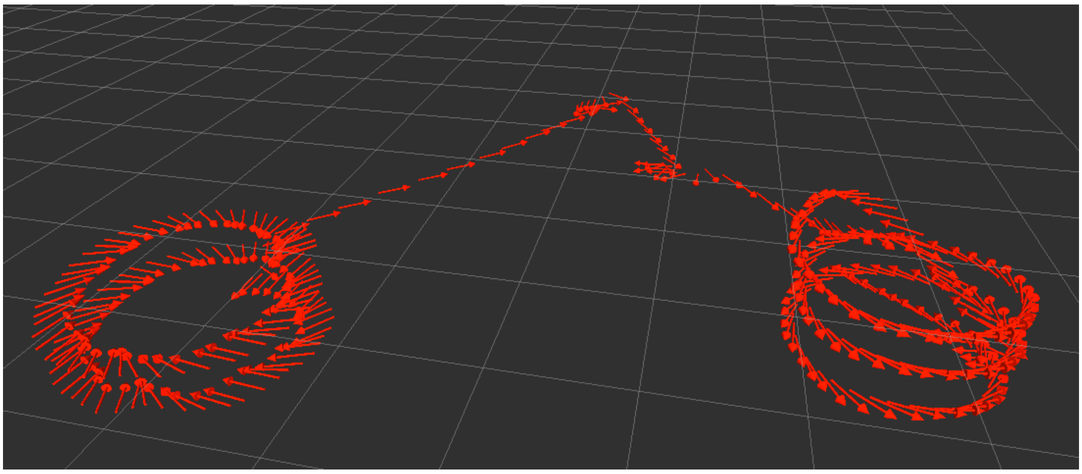

Fig. 8. The full path of the robot Nessie AUV in RViz, the ROS visualisation system. Each square of the grid is 1m long. The recorded path starts on the left, when the robot perform an inspect of the pillar, then moves to inspect a second location, finding out that it was not of interest, to finally arrive to the third location, recognise a pillar and perform an inspection. Note that the last inspection follows a different behaviour, due to a fault injected in the system on a lateral thruster.

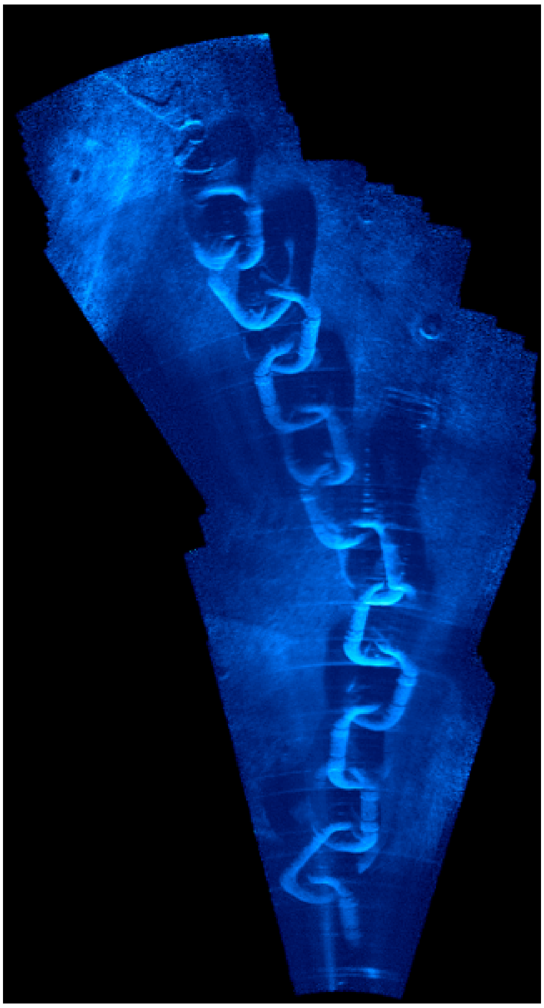

Fig. 9. A sonar mosaic of the chain.

4.3 Task C: Autonomous grasping and turning of a valve from a swimming, undocked vehicle

In this task emphasis was given to external disturbances and the related challenges. A robot arm is at the front of

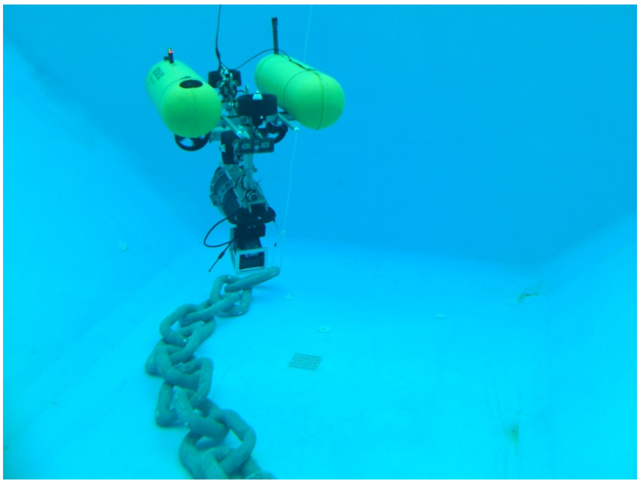

Fig. 10. Girona 500 AUV performing a chain inspection task.

the vehicle and the goal is to successfully locate a panel and turn a valve positioned on the panel. A selection of valve heads are exposed, each with a T-bar attached for grasping. The vehicle needs to identify the state of the valves (open, close, in-between) from the T bar orientations, and if appropriate, use the robot arm to grasp the correct valve and open it. The vehicle does not dock, because there are no docking bars on the panel. Successful tests were performed in the CIRS tank, as in Fig. 12. In the Figure, the panel is positioned in front of the vehicle, with two big thrusters on the left side, in order to create disturbances and test the robustness of the algorithms.

5. CONCLUSION

This paper has presented the challenges which the FP7 Project PANDORA has addressed in the last three years, focusing on persistent autonomy. Current existing autonomous systems require frequent operator intervention. The focus of Pandora is to enhance the long-term autonomy of AUV missions, through increased cognition, at all

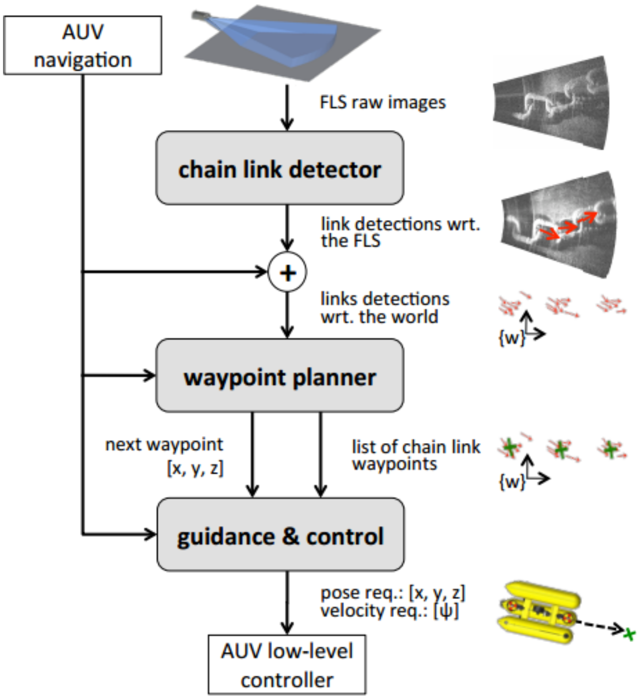

Fig. 11. Diagram illustrating the different steps of the chain following framework.

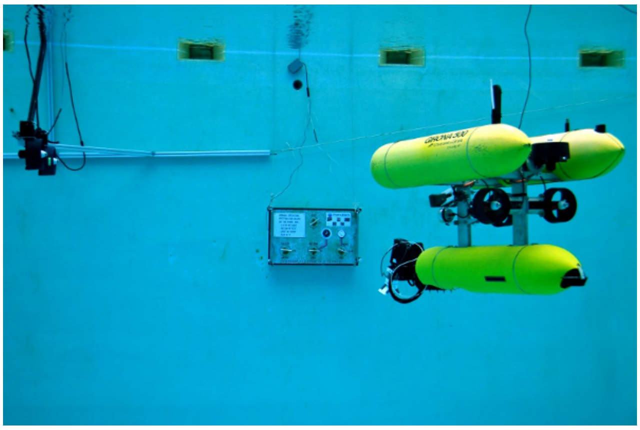

Fig. 12. Girona 500 AUV performing a valve turning task.

the levels of abstraction. Research into several areas like knowledge representation, navigation, planning, learning and control have been applied to three different scenarios: inspection of underwater structures, chain cleaning and valve turning. Successful tests have been arranged with both Girona 500 AUV and Nessie AUV, in Girona, Edinburgh and Fort William. The vehicles were not only able to fulfil the task in laboratory conditions, but unexpected external disturbances and internal failures have been taken into account. An open sea test is planned at Fort William to fully validate the inspection scenario in real conditions, in presence of strong tides and real-world challenges.

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REFERENCES

Seyed Reza Ahmadzadeh, Arnau Carrera, Matteo Leonetti, Petar Kormushev, and Darwin G. Caldwell. Online discovery of AUV control policies to overcome thruster failures. In *Proceedings of IEEE ICRA'14 Hong Kong*, 2014.

Michael Cashmore, Maria Fox, Tom Larkworthy, Derek Long, and Daniele Magazzeni. Planning inspection tasks for AUV. In *Proceedings of IEEE Oceans'13 San Diego, USA*, 2013.

Michael Cashmore, Maria Fox, Tom Larkworthy, Derek Long, and Daniele Magazzeni. AUV mission control via temporal planning. In *Proceedings of IEEE ICRA'14 Hong Kong*, 2014.

N. Hurtos, X. Cufi, and J. Salvi. A novel blending technique for two-dimensional forward-looking sonar mosaicing. In *Proceedings of IEEE Oceans'13 San Diego, USA*, 2013.

Natalia Hurtos, Narcis Palomeras, Arnau Carrera, Marc Carreras, Charalampos P. Bechlioulis, George C. Karras, Shahab Hesmati-alamdari, and Kostas Kyriakopoulos. Sonar-based chain following using an autonomous underwater vehicle. In *Proceedings of IEEE IROS'14, Chicago, USA*, 2014.

Nawid Jamali, Petar Kormushev, Arnau Carrera, Marc Carreras, and Darwin G. Caldwell. Underwater robot-object contact perception using machine learning on force/torque sensor feedback. In *Proceedings of IEEE ICRA'15 Seattle, USA*, 2015.

G.C. Karras, C.P. Bechlioulis, M. Leonetti, N. Palomeras, P. Kormushev, K.J. Kyriakopoulos, and D.G. Caldwell. On-line identification of autonomous underwater vehicles through global derivative-free optimization. In *Proceedings of IEEE IROS'13*, 2013.

F. Maurelli, Z. Saigol, D. Lane, M. Cashmore, B. Ridder, and D. Magazzeni. On AUV actions to correctly label world information. In *Proceedings of IEEE-MTS Oceans'14, St. John's, Canada*, 2014a.

Francesco Maurelli, Zeyn Saigol, Georgios Papadimitriou, Tom Larkworthy, Valerio De Carolis, and David Lane. Probabilistic approaches in ontologies: joining semantics and uncertainty for AUV persistent autonomy. In *Proceedings of IEEE-MTS Oceans'13, San Diego, USA*, 2013.

Francesco Maurelli, Zeyn Saigol, and David Lane. Cognitive knowledge representation under uncertainty for autonomous underwater vehicles. In *Proceedings of IEEE ICRA'14 IEEE Hong Kong, Workshop on Persistent Autonomy for Underwater Robotics*, 2014b.