The underwater environment: a challenge for planning *

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Abstract

This paper reviews the applications and challenges of robotic systems in the underwater domain. It focuses on the challenges for achieving embedded situation awareness, adaptive trajectory planning and adaptive mission planning. These are required elements for providing true autonomy for delegation of tasks to unmanned underwater vehicles. The paper analyses current approaches to tackling these challenges and how planning plays a vital role in overcoming them. It includes a description of some key applications and future concepts of operations.

Introduction

In the last few decades, increasing interest in oceans has resulted in unprecedented attention being focussed on them. Although they cover 71% of the Earth's surface, humankind has sent more astronauts to the Moon than scientists to the deepest parts of our seas. It was almost 10 years after reaching the surface of the Moon, that the deepest parts of the oceans were finally reached. Since then, goverments and industry have become more and more interested in understanding and managing our planet and they have realised how important the underwater regions, two thirds of the total Earth's surface, are. Nowadays, it is not only the need to discover, but also to observe, map and protect our oceans that motivates further exploration of underwater regions.

Unfortunately, access to these regions is not straightforward. The underwater environment is a hostile environment for humans and human technology. It can challenge some of the capabilities that are now taken for granted in other domains such as the Earth's surface, the atmosphere or outer space. Some of the most representative and specific challenges underwater are high pressure, corrosion and signal processing issues related to data transmission and sensing.

Even though the underwater domain presents such challenges, several maritime disciplines still require access to this environment. The most relevant ones are:

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- **Oceanography:** Scientists are faced with the need of gaining access to the most remote parts of the oceans, from deep trenches to fresh water lakes under the polar ice caps. They have to collect information in order to be able to understand issues such as climate change, the melting of the polar ice caps and to forecast weather conditions, hurricanes and tsunamis.
- **Energy industry:** In current offshore oil fields the tasks of Inspection, Repair and Maintenance (IRM) comprise up to 90% of the related field activity. This inspection is dictated by the vessels availability and the weather conditions. Additionally, the deep sea is still un-exploited. Gaining access to these deeper levels can provide access to new sources of minerals and energy.
- **Military:** A priority to current Navy operations is to maintain clear access to ship passages and to protect vessels, harbours and coastal waters. Achieving these capabilities without compromising personnel safety due to foe actions is still unsolved.

For all these disciplines, robotic platforms are proven to be very useful in de-risking human activity in the hostile underwater environment. The main challenges that robotic systems have to deal with underwater are:

- **Power** : Robots are highly dependant on their battery life in a domain without possibility of extending it from other external sources.
- **Communication** : Sound is the media use for sensing and communicating underwater. Low bandwidth, long delays and high-power requirements impose many restrictions.
- **Perception** : Visual methods are poor while acoustic methods come with many false positives. They are affected by temperature, pressure and salinity making them very noisy. Range is inversely related to the frequency and normally quite reduced (see Fig. 1). Additionally, raw sensor data has to be ultimately processed into conceptual knowledge in order to build the awareness of the environment.
- **Navigation** : The underwater environment is a GPS-denied area. Existing underwater maps are still quite innacurate. Together, these make localization and orienteering for navigation a very hard problem.

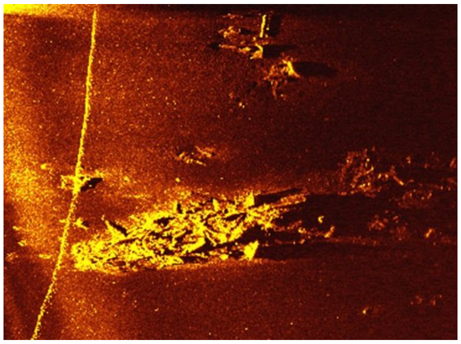

Figure 1: Acoustic image of 50m range of a WWI U-boat sunk in Hoxa Sound, Scapa Flow (courtesy of SeeByte Ltd.).

- **Delegation**: Autonomous adaptation of different tasks to changes in the environment has not yet been fully achieved. Without it, it is necessary that the operator remains in the loop, observing and taking decisions. Autonomous adaptation to sensed changes is necessary to gain the operator's trust and acceptance and for them to delegate tasks to the robotic platform (Johnson, Patrón, and Lane 2007).

Although new solutions are already being developed to extend power autonomy and communication requirements, the other three issues (perception, navigation and delegation) are still a real challenge for achieving true autonomy in robotics in the underwater environment. This paper describes each of these challenges and provides an overview on how reasoning tools and autonomous planning approaches can contribute to overcoming them.

Robotic platforms

Unmanned underwater vehicles can be classified in *Remote Operated Underwater Vehicles* (ROVs) (see Fig. 2), *Autonomous Underwater Vehicles* (AUVs) (see Fig. 3) and *Underwater Gliders*. They differ on the power capability, power endurance and the task complexity that they have been designed for.

Underwater vehicles have become a standard tool for data gathering for Maritime applications. In these environments, mission effectiveness directly depends on vehicle's *operability*. Operability underlies the vehicle's final availability, affordability and acceptance. Two main vehicle characteristics can improve the vehicle's operability: *reliability* relates to vehicle failures due to the internal hardware components of the vehicle, and *survivability* relates to vehicle failures due to external factors or damages.

Each of these characteristics can be improved by providing autonomous adaptation of the mission plan and autonomous adaptation of the trajectory plan respectively. Both require access to the correspondent levels of perception in order to build their own situation awareness.

In current implementations, the human operator constitutes the decision making phase. When high-bandwidth communication links exist, the operator remains in the loop during the mission execution. Examples of this approach are existing ROVs. However, when the communication is poor, unreliable or not allowed, the operator tries, based only on the initial orientation or expertise, to include all possible behaviours to cope with execution alternatives. This has unpredictable consequences, in which unexpected situations can cause the mission to abort and might even cause the loss of the vehicle. Examples of this architecture are current implementations for AUVs and gliders.

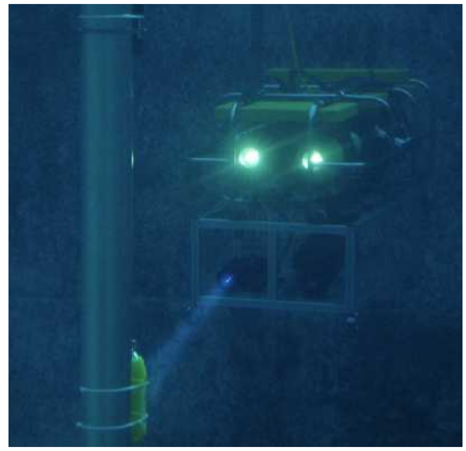

Figure 2: Typical ROV inspection operation of a riser with a fluorometer sensor.

Figure 3: AUV recovery after finishing a mission (courtesy of SeeByte Ltd.).

Towards adaptive autonomy

Autonomous adaptation can release the operator from decision making tasks at the trajectory and mission planning levels. These, in consequence, can require less communication with the consequent power saving. Adaptation plays an important role in providing autonomy. The aim is to be effective and efficient and a plan costs time to prepare. This time has been already invested once (to compute the plan that is now failing), so it might be more efficient to try to reuse previous efforts by repairing it. Also, commitments might have been made to the current plan: trajectory reported to other intelligent agents, assignment of resources or assignment of part of mission plan to executors, etc. Repairing an existing plan ensures that as few commitments as possible are inval-

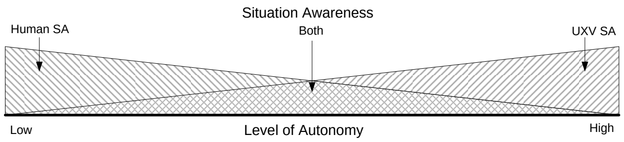

Figure 4: Human and AUV SA across the levels of autonomy

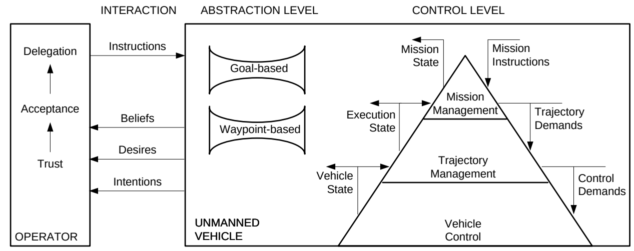

Figure 5: Levels of control related to the level of abstraction of knowledge for operator's delegation of tasks to unmanned vehicles.

idated. Finally, several planners (usually autonomous and human planners combined) could be performing together to achieve the goals. In such cases, it is more likely that a similar mission plan will be accepted by the operator than one that is potentially completely different.

Autonomous adaptation requires an autonomous understanding of the environment. The human capability of dealing and understanding highly dynamic and complex environments is known as *situation awareness* (SA_H). SA_H breaks down into perception of the environment, comprehension of the situation and projection of the future status. Decision making occurs in a cycle of observe-orient-decide-act ($OODA$) (Boyd 1995). The *Observation* component corresponds to the perception level of SA_H. The *Orientation* component contains the previously adquired knowledge and understanding of the situation. The *Decision* component represents the SA_H levels of comprehension and projection. This last stage is the central mechanism enabling adaptation before closing the loop with the final *Action* stage. Note that it is possible to take decisions by looking only at orientation inputs without making any use of observations.

Based on the autonomy levels and environmental characteristics, SA_H definitions can be directly applied to the notion of *unmanned vehicle situation awareness* (SA_V) (Adams 2007). Increasing the levels of situation awareness for individual unmanned vehicle systems (SA_S) can help the transfer from current full human control to fully autonomous unmanned capabilities (see Fig. 4). This knowledge representation is the focus of the next section.

Knowledge representation and transfer

At present, knowledge representation is embryonic and targets simple mono-platform and mono-domain applications, therefore limiting the potential of multiple coordinated actions between agents. Consequently, the main application for autonomous underwater vehicles is information gathering from sensor data. In a standard mission flow, data is collected during mission and then post-processed off-line.

However, in order to be able to let decision making technologies evolve towards providing higher levels of autonomy and control, embedded service-oriented agents require access to higher levels of knowledge representation or abstraction (see Fig. 5). These higher levels will be required to provide knowledge representation for contextual awareness, temporal awareness and behavioural awareness.

Two sources can provide this type of information: the domain knowledge extracted from the original expert (orientation) or the inferred knowledge from the processed sensor data (observation). In both cases, it will be necessary for the information to be stored, accessed and shared efficiently by the deliberative agents while performing a mission. These agents, providing different capabilities, might even be distributed among the different platforms working in collaboration.

Semantic frameworks have recently raise interest providing hierarchical distributed representation of knowledge for multidisciplinary agent interaction (Patrón et al. 2008a). They provide with a common machine understanding representation of knowledge between embedded agents that is generic and extendable. They also include a reasoning interface for inferring new knowledge from the observed data and knowledge stability by checking for inconsistencies. These frameworks improve local (machine level) and global (system level) situation awareness and context for mission and trajectory behavior. They can therefore act as enablers for autonomy and on-board decision making.

There are currently several institutions and consortiums developing standards for knowledge representation under these frameworks. Particular attention is taking the effort describing the concepts and relationships for the domains of unmanned platforms (jau 2008) and the underwater environments (mmi 2008). An example is shown in Fig. 6.

Trajectory planning

Navigation and mapping

Existing geographical information for trajectory planning can be represented using knowledge-based frameworks. However, mapping of the environment depends on the uncertainty in the position of the vehicle when the obstacles are observed and mapped. Navigation in unknown underwater environments entails high levels of uncertainty.

Geolocating a vehicle on the World's surface can be accurately performed by using Global Positioning System (GPS) receivers. But GPS does not work underwater as the radio signals on which it depends cannot pass through water. *Dead reckoning* is the standard technique used underwater and involves use of Inertial Measurement Units (IMUs), a combination of accelerometers and gyroscopes. Abbe error, magnification of angular error over distance, can be detrimental to dead reckoning. Inertial Navigation Systems (INS) integrate accelerations and rates to provide a Kalman filtered navigation solution. They use inputs from acoustic transmitters and receivers to pin-point the platform's location. How-

Core Ontology $TBox/ABox$ for MCM Mission
• *CAD Module* - hasRequirement: Sidescan - isCapableOf: Mine-like objects detection, • *CAC Module* - hasRequirement: Mine-like objects detection - isCapableOf: Mine-like objects classification, • *CAD/CAC Payload* - hasSoftware: CAD/CAC Module, • *Platform* - hasPayload: Payload, ...
$\star$ MarineSonic $\in$ Sidescan, $\star$ SBCAC $\in$ CAC, $\star$ SBCAD $\in$ CAD, $\star$ SB337 $\in$ CAD/CAC Payload - hasSoftware: SBCAD & SBCAC, $\star$ Remus337 $\in$ Platform - hasHardware: MarineSonic - hasPayload: SB337,...

Planning Application Ontology $TBox/ABox$ for MCM
• Action - hasRequirement:, hasPlatform:, • Mission - hasRequirement:, hasPlatform:, ...
$\star$ Explore $\in$ Action - hasRequirement: Sidescan driver, $\star$ Detect $\in$ Action - hasRequirement: Mine-like objects detection, $\star$ Classify $\in$ Action - hasRequirement: Mine-like objects classification, $\star$ Clearance $\in$ Mission - hasRequirement: Mine-like object classification, ...

Figure 6: Example of platform domain and mission planning application description for a mine counter measure (MCM) underwater scenario.

ever, the range of these systems is limited to no more than a few nautical miles thus restricting the vehicles autonomy. A better approach involves aiding the INS with a Doppler Velocity Log (DVL) sensor that measures the displacement rate over the seabed. No matter how accurate the sensors are, the errors in these systems grow with time and the platform becomes progressively lost unless it is able to obtain external references from acoustic devices or from a GPS receiver on the surface. This uncertainty in the vehicle's location gets passed to the geolocation of the observed elements in the environement during the mapping process.

A promising alternative is Simultaneous Localisation And Mapping (SLAM). Using SLAM a platform maps the environment and uses the map to localise itself in it. The map can be georeferenced if the platform maintains an estimate of its absolute position when the process of mapping is started. A recent development has shown that it is possible to post-process and smooth the SLAM solution using the Rauch-Tung-Striebel smoother (see Fig.7). This new technique, coined SLAM-RTS, has been used to create better maps of the environment and to help the trajectory planning systems to accurately locate the sensed obstacles in the map (Patrón and Tena-Ruiz 2006).

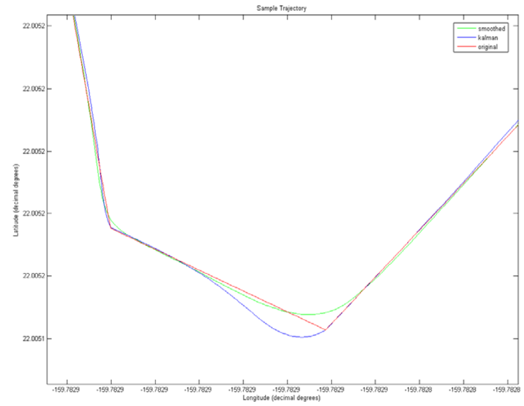

Figure 7: Original, Kalman filtered and RTS smoothed trajectory of an underwater vehicle.

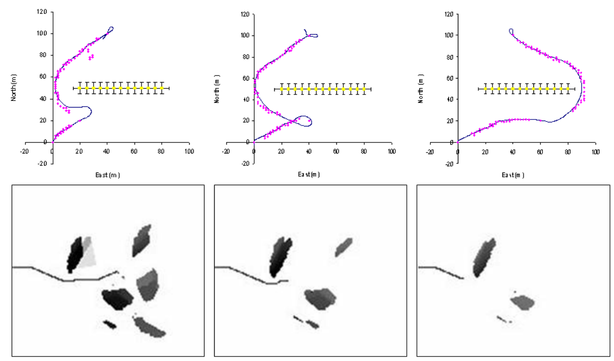

Figure 8: Top: Net avoidance trajectories obtained with the dynamic model simulator. Bottom : Three sequential observations of the local map with trail showing planned forward trajectory to achieve the waypoint in a real scenario.

Obstacle avoidance

Once the navigation and mapping error has been bounded, an adaptation of the trajectory and waypoints is required during mission when unexpected events on the planned trajectory are sensed. Collision avoidance and escape is a key capability for underwater vehicle navigation.

Traditional approaches to collision avoidance and escape are purely reactive and usually involve an algorithmic formulation of response dictated by the objects geometries and locations and the relative location of the vehicle. Recent approaches in rules of collision (Benjamin et al. 2006) and obstacle avoidance and escape scenarios (Evans et al. 2007) have focused on reducing susceptibility by looking at the adaptation of the vehicle's trajectory plan. These deliberative behaviours provide the defined and bounded event responses that link to geometric methods of trajectory planning.

At the trajectory planning level, lifelong planning incremental search methods have been found to decrease computation time while still locating the shortest trajectory between vehicle and goal (Koenig, Likhachev, and Furcy

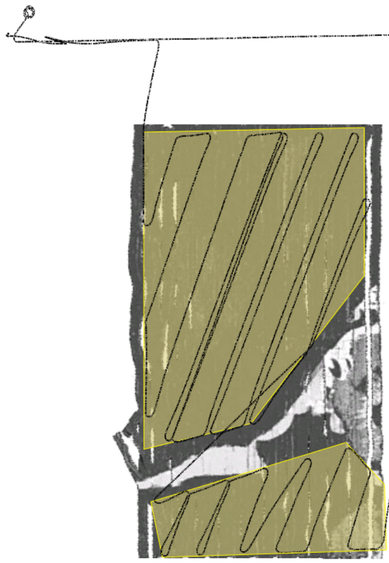

Figure 9: AUV survey of two seabed areas with an adaptive mission planner capable of reacting to water currents and sensor faults.

2004). Instead of starting from scratch every time a trajectory must be adapted, they reuse data found in previous searches to save on computation time. Wave propagation techniques can also provide with smoother and shorter trajectories than classic discrete search approaches. This fast marching methods are capable of dealing with uncertainty, dynamic objects and kinematics of the vehicle during the adaptation process (Pêtrès et al. 2007). A real application of these techniques in the underwater environment is shown in Fig. 8.

Mission planning

Single platform

Current mission plan solutions for underwater platforms are procedural and static (Hagen 2001). If behaviors are added (Pang et al. 2003), they are only to cope with possible changes that are known a-priori by the operator. In order to achieve higher levels of autonomy, plan adaptability should be available not only to procedural waypoint-based approaches on trajectory planning but also to a declarative goal-based solution for adaptive mission planning.

On a goal-oriented command and control, decision tools can be developed providing support for adaptive data sampling, optimization of resources and fault recovery capabilities of the platform (Bellingham, Kirkwood, and Rajan 2006).

The potential benefits of the planning capabilities for adaptive data sampling have been studied by Rajan (Rajan et al. 2007) and Fox (Fox et al. 2007). An example of this application is the T-Rex system, an adaptive planning architecture with notions of timing and onboard resource management responsiveness to opportunistic science events (McGann et al. 2007).

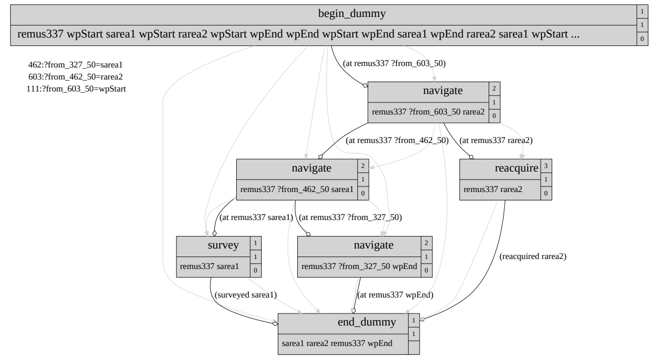

Figure 10: Partial plan representation of an underwater mission.

In a similar way, fault-tolerant mission planning adaptation can also contribute towards providing more mission flexibility and robustness. When active and passive measures fail to protect the vehicle, or unexpected hardware failures occur, the focus of the mission should shift to 'reconfigure' itself to use alternative combinations of the remaining resources (see Fig. 9). In the underwater environment, autonomous embedded *recoverability*, is a key capability for vehicle's endurance. This can be achieved via adaptation of the vehicle's mission plan (Patrón et al. 2008c). The aim is to provide with a mission plan as close as possible to the original. In such case, plan optimality during the adaptation process can be sacrified for plan stability (Fox et al. 2006).

This level of control can also benefit from the use of knowledge frameworks. Adaptation is limited to the quality and scope of the available information. Therefore, to adapt mission plans due to unforeseen and incipient faults, it is required that accurate information is available, to recognize that a fault has occurred and deduce the root cause of the failure.

Current robotic solutions are generally equipped with Failure Diagnosis and Detection (FDD) systems based on damage control that results in the vehicle resurfacing in the event of any fault in the system. But future operations will require long-endurance unattended systems that operate even while being partially damaged or while having constrained capabilities. Hence, it is important to develop system which not only detect failure in the component but also provide mission plan modules capable of adapting and recovering from these failures. This exchange of meaningful and reliable knowledge between FDDs and mission planners can leverage on the use of semantic knowledge frameworks.

Once the knowledge has been transferred from the FDD, the adaptation approach combines robust execution and mission plan repair in order to maximize system performance and response time. Two levels of repair are possible. If the fault coming from the FDD is incipient or non-critical, a repair at the executive level is performed. This entails adapting the intances and parameters of the action performing the task without changing the action itself. If a critical fault on a component is diagnosed, a repair at the plan level is performed that changes the action requiring of the component

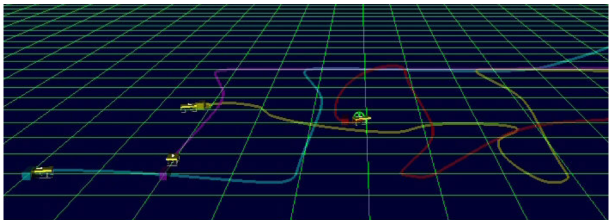

Figure 11: Fleet of unmanned underwater vehicles performing a survey pattern task in collaboration for an Autonomous Target Recognition (ATR) scenario.

and the constraints on the action. During this decision making process, a combination of refinement and unrefinement phases of the constraints of a partial ordered mission plan can be used (Patrón et al. 2008b) (see Fig. 10).

Collaborative planning

Mission plan adaptation can be extended to multiple platforms. The potential benefits of multi-vehicle operations include force-multiplier effects, redundancy avoidance and the utilisation of heterogeneous vehicle configurations to reduce risk to expensive assets. But to achieve the full benefits, suitable architectures that facilitate true cooperative autonomous planning for task splitting and allocation must be realised (Evans et al. 2006).

In this case, it is necessary to extend the single vehicle mission plan recovery to a mission plan recovery for a group or team of vehicles performing a collaborative mission. A shared situation awareness is required for the team of vehicles (SA_T) to which every team member possess the SA_S required for its responsibilities (Cartwright et al. 2007). The main challenge in this case is to deal with the acoustic communication limitations associated to the underwater environment (Sotzing, Evans, and Lane 2007).

Sensing networks and beyond

The elements previously described are the most immediate requirements for unmanned platforms in the underwater domain. However, other long-term subsea applications are appearing posing other problems and challenges. The planning community can help to overcome them.

Ocean observatories in oceanology, all year round subsea field inspection for the energy industry and continous harbour and coast patroling for the Navy are emerging, requiring a more permanent presence of robotic and sensing tools underwater. These applications are demanding underwater networks of fixed sensors in combination with fleets of AUVs and gliders. These sensing webs require decision making algorithms in order to be able to optimize the management of heterogeneous assets and resources, to couple observation systems and ocean models, to minimize error in the reconstruction of ocean fields and to provide fast dynamic response to events.

Conclusion

Robotic platforms are helping marine applications to gain routine and permanent access to the underwater environment. However, challenges related to this domain require the development and integration of more evolved embedded tools that can raise the platform's autonomy levels while maintaining the trust of the operator. This paper shows how knowledge representation, reasoning and planning tools can help to overcome these challenges. The study describes current approaches to situation awareness, trajectory planning and mission planning for underwater vehicles. It finishes by highlighting the long-term scenarios that can also benefit from planning tools.

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