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Autonomy in Marine Archaeology

Øyvind Ødegård(1, 2)
oyvind.odegard@ntnu.no
Stein M. Nornes(1)
stein.nornes@ntnu.no
Martin Ludvigsen(1)
martin.ludvigsen@ntnu.no
Thijs J. Maarleveld(3)
t.maarleveld@udu.dk
Asgeir J. Sørensen(1)
asgeir.sorensen@ntnu.no

1 Centre for Autonomous Marine Operations and Systems (AMOS) Department of Marine Technology, Norwegian University of Science and Technology, Norway
2 Department of Archaeology and Cultural History, University Museum, Norwegian University of Science and Technology, Norway
3 Department of History, Maritime Archaeology Programme, University of Southern Denmark

Abstract: After what oceanographers have called 'a century of undersampling', the marine sciences are now benefiting from tremendous technological advances in sensors and sensor platforms. Efficient exploration of the deep or remote marine environments depends on the use of underwater robotics, particularly untethered Autonomous Underwater Vehicles (AUVs) that can be sent out on missions covering large areas and return with data from multiple sensors. As technological developments allow AUVs to be deployed on long duration missions (months), the need for robust autonomous guidance, navigation and control systems become evident. For long duration missions in areas that prohibit human involvement (e.g. ultra-deep or under ice), it will be of interest for marine archaeologists to have an AUV that can find as many wrecks or other traces of cultural heritage on the seabed as possible. A hypothetical long duration AUV survey implementing archaeological mission objectives is described and discussed.

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Introduction

Climate change and enabling technologies are driving forces for an increased attention to mapping and expanding our understanding of the oceans. Industry and management have common needs for knowledge and data to better exploit marine resources both economically and environmentally. This is also true for management of underwater cultural heritage. The lack of data from the underwater environment has become a major problem for the discipline. True: exemplary research can usefully focus on those sites for which evidence exists. However, the quantitative lack of data affects the way research issues can be resolved and is particularly dramatic in relation to present management schemes. This is the more urgent since management, including cultural heritage management and the management of research funding have become addicted to quantitative control (Anthony and Govindarajan 2007). After a century of undersampling, new technologies show promising potential for mapping larger areas with high temporal and spatial coverage and resolution helping scientists to acquire data relevant and appropriate for questions that previously were difficult nor even impossible to answer (Nilssen et al. 2015).

The new technologies are sensors such as Synthetic Aperture Sonar (SAS) (Hansen 2011) and Underwater Hyperspectral Imaging (UHI) (Johnson 2013), advanced sensor platforms, increased processing abilities and progress in research on control methods for autonomy. This development seen in light of the holistic principles behind emerging Ecosystem Based Management models (de la Mare 2005) should enable large scale data gathering operations in the ocean space to integrate archaeological aspects without much ado.

On land, in relation to occupation sites, and in relation to sites of a monumental character a quantitative body of observations has consistently been built up by populations that run in the tens of millions. Subsequently, over more than 200 years, these observations have been systematized by antiquarians and archaeologists who had relatively easy access, and who could make sure that observations were reliably corroborated. Under water and in relation with marine sites this is far less the...
case. Even though the last 70 years have seen the discipline of marine archaeology develop, the intensity of observations lags far behind. Apart from systematic survey – and even there – observations are limited to where people go, which stands in no relation to the sheer extent of the underwater landscape. For various reasons many observations never enter the archaeological record (Maarleveld 2010). Moreover, many underwater observations are uncorroborated, as corroboration is relatively impracticable in the underwater environment. However, it begs the question whether vague data is data at all.

While there are considerable advances made in control systems, navigation system and manipulators for remotely operated vehicles (ROVs) that will also benefit ocean space mapping (Sorensen et al. 2012) this paper will focus on untethered autonomous underwater vehicles (AUVs). Because of the exponentially growing amount of data new sensors can provide, an important challenge is to reduce the amount of data describing ‘uninteresting observations’, and on the other hand get as much as possible from ‘interesting observations’. This is of course due to storage capacity, processing time and energy budget. Having robots that stop, turn on additional sensors, lights, and do detailed surveying only when they have found something worth investigating, will save energy to do longer missions and cover larger areas.

In this paper we will be discussing future missions to explore the ocean space that are based on certain assumptions. For long duration surveys in deeper waters, the costs of revisiting areas are very high. We will therefore be assuming that these are ‘one shot’ operations with only one chance to get it right, and revisiting or inspecting objects of interest (OOI) later is not considered an option. Another assumption is that purely archaeological missions are not likely to happen. There probably will be interdisciplinary cruises/surveys with multiple stakeholders involved including archaeology as one of them. As limited available energy is the main constraint for AUV operations, we assume that resources allocated to archaeology must be negotiated, and that a high number of false positives, is a negative argument regarding archaeology.

As technological developments allow AUVs to be deployed on long duration missions (months), the need for robust autonomous guidance, navigation and control systems become evident. Intelligent control command and task execution with obstacle avoidance, fault-detection and diagnosis as a basis for reconfigurable control re-planning of path and missions will be necessary in order to improve capabilities to operate in an unstructured environment with little or no a priori knowledge. In the years to come the field of artificial intelligence and learning systems as driven forward in the field of software science will strengthen the interactions between top-down and bottom-up approaches towards improved autonomy and more intelligent systems and operations. Adaptive planning and strategical and tactical decision making are methods that have already been used successfully by marine sciences and for navy purposes. This paper will present some examples of these methods in a discussion of (and how) they can be adapted to archaeological applications. The paper aims to identify and define some challenges regarding autonomy in marine archaeology, and to demonstrate the importance of debating them.

1 AUV

Autonomous Underwater Vehicles (AUVs) are untethered robots that can operate independent of human operators at different levels of autonomy. AUVs come in many different shapes and sizes. For long duration missions covering large areas, slender bodied torpedo shaped vehicles with one propeller are commonly used (Hobson et al. 2012). An AUV typically consists of battery or energy cell for power, a propulsion unit, communication unit, navigation and payload sensors and computers (Fig. 1). Typical navigational sensors

**Fig. 1. Outline of AUV anatomy.**
are Doppler Velocity Logger (DVL), Current Temperature and Depth (CTD), Compass and Motion Reference Unit (MRU). Typical payload sensors are long range sonar systems like Side Scan Sonar (SSS), Synthetic Aperture Sonar (SAS) and Multi Beam Echo sounders (MBE). Sub Bottom Profilers (SBP), magnetometers, different types of cameras and other instruments are deployed for measuring bio-geo-chemical properties. For a description of typical payload and navigation sensors see Sorensen and Ludvigsen (2015). Even though we distinguish between navigational sensors and payload sensors in the autonomy architecture, it should be mentioned that data from several sensors can be used for multiple mission objectives, and are not exclusive for one particular purpose.

1.1 Control system

In addition to hardware an AUV is completely dependent on a control system to operate. The control system is the ‘brain’ of the robot, and commands and coordinates every single part of the AUV to make it behave in accordance with a mission plan. Complex mission plans may require many parallel or sequential tasks to be performed interdependently, often with conditional choices for the next action. If an AUV is to operate in an environment with many unknowns and uncertainties, which typically characterizes the marine environment, an intelligent control system will increase the chances for success in performing its mission. Since the late 1980s there have been great advances in the research field of intelligent control. The challenges of introducing Artificial Intelligence (AI) and autonomy into the predominantly mathematical field of conventional control theory was recognized early (Meystel, 1989), and the necessity for multi- or interdisciplinary work efforts were acknowledged (Antsaklis et al. 1989; Zeigler 1990). The three layered hybrid architecture emerged as a successful framework for autonomy, and became a standard approach to autonomy for mobile robots (Gat, 1998). Many of the most successful systems today have evolved from these early models, and have similar divisions. The three layers all have important roles to play with regards to autonomy. The following AUV autonomy framework (Fig. 2) is based on the autonomy architecture presented in Sorensen and Ludvigsen (2015). At the top is the mission planning layer where the mission objective is defined and the mission is planned with tasks to fulfill the mission goal(s). Subject to contingency handling, any input from payload sensor data analysis and any other input from the autonomy layer, the mission may be replanned. This layer also manages and maintains a world model by continuous updating from sensor data. The guidance and optimization layer translates these tasks into sequences of behaviours that are carried out by distributing commands to actuators and sensors in the control execution level.

1.2 Autonomy

Discussing autonomy from an end-user perspective can bring untraditional problems into an established discourse, as concepts can represent different meanings in different disciplines (Bal 2009). The need for precise taxonomy to avoid
misunderstandings is important. The terms Autonomy and Level of Autonomy (LOA) are used to describe the relationship between human and machine, and are often expressed along a scale with increasing machine control and less human interference. Different models are used since robot/human relationships can be very diverse and take on quite different forms. Some models are very simplistic with few levels, and short descriptions of each level, while other are more intricate with several dimensions necessary for describing complex relationships, e.g. involving contextual factors like environment and data processing. A good overview of autonomy taxonomy can be found in Vagia et al. (in press).

Hagen et al. (2009) links levels of autonomy for AUVs to their performance in energy autonomy, navigation autonomy and decision autonomy. To see autonomy in relation to tasks, and not just as a relationship between human and machine, we need to investigate how high level archaeological goals can be formulated in an autonomy layer, but also how marine archaeological practice can be translated into meaningful actions and behaviours for the robot.

For short term missions in relatively known environments, uncertainties can be handled by e.g. simple IF-THEN-ELSE rules (Gat, 1998). The programmer can predict possible events, and have the robot to act based on rules encompassing these events. This can involve multiple conditions, creating a more solid basis for decisions. However, as the number of conditions grows the conditional variations grow exponentially, and the purely logical decision model becomes exceedingly complex very fast. The robot now needs to deliberate combinations of events, both in its environment and regarding its own state, that are beyond practical predictability. This problem is especially relevant for longer missions in unknown environments.

### 1.3 SLaM

Simultaneous Localization and Mapping (SLaM) addresses the problem of constructing a spatial map of the environment around a mobile robot while simultaneously utilizing this map to calculate the position of the robot relative to this map (Siciliano and Khatib 2008).

Efficient method for SLaM is generally regarded as one of the most important problems to solve in the pursuit of building autonomous mobile robots capable of operating unassisted in unknown environments for a prolonged period of time with limited access to external navigation systems such as acoustics of surface based satellite systems. With global position updates such as GPS being unavailable underwater one would often rely on dead reckoning methods for navigation. In such systems small measurement errors from navigation sensors will accumulate over time causing the estimated position of the vehicle to drift. With SLaM, a vehicle revisiting an area mapped earlier in the mission can use the new position calculated from the map to counteract this time related drift. This is often referred as ‘closing the loop’ and bound the error drift.

An autonomous vehicle will also be limited by both power consumption and data storage. To map large areas efficiently, it is often beneficial to do an initial coarse resolution mapping and return to smaller areas with features and objects of interest (OOI) for a higher resolution mapping. Doing this on a single dive is known as adaptive replanning (Wig et al. 2012).

Obviously, the map built using SLaM will be highly beneficial for relocating the features and OOI for re-examining.

SLaM methods have now reached a state of considerable maturity (Durrant-Whyte and Bailey 2006; Bailey and Durrant-Whyte 2006). Several successful implementations have been demonstrated, ranging from structured man-made environments (Ribas et al. 2008) to drowned coral reefs (Williams et al. 2009) to visual mapping of the RMS Titanic (Eustice et al. 2005). Newer research (Kim and Eustice 2014) is also moving from passive SLaM where the vehicle follows a predetermined path, to active SLaM where the path is modified to improve both map building and localization performance.

The main obstacle for SLaM has traditionally been computational complexity. With continuous improvements in computational power and research into new algorithms, the field has grown considerably the last decade, and is likely to continue improving.

### 2 Archaeological survey

For long duration missions in areas that prohibit human involvement (e.g. ultra-deep or under ice), it will be of interest for marine archaeologists to have an AUV that can find as many wrecks or other traces of cultural heritage on the seabed as possible. The AUV should return with good data from each site that can serve as a foundation for decision making regarding management issues, or as material for research and knowledge production in case the site will not be revisited again. This is a comprehensive mission objective, and one must expect to make many compromises both in terms of what can be done, and how it can be done. Since an exhaustive high resolution multi sensor mapping of every inch of the seabed is not feasible with current technologies, we must introduce elements of deliberation and choices into the mission plan that will reduce the amount of work to be done, and have the robot only spend time and resources on sites that are likely to be of interest. A high level formulation of this mission objective can be divided into three missions: Mission 1 – Detect; Mission 2 – Verify and Mission 3 – Record (Fig. 3). The missions are sequentially dependent, mission 2 will only be performed if mission 1 produces waypoints, likewise mission 3 will only be performed if mission 2 result in any Objects of interest (OOI).

To see how these missions can best be implemented into the control architecture of an AUV, we must decompose/deconstruct each mission into tasks that better matches the behaviours AUVs typically can perform. This requires the archaeologist to see marine archaeological praxis independent of the methodological and cognitive constraints typical for the tools commonly available today, and instead adopt and investigate the possibilities offered by the perceptive and operational abilities and constraints of the AUV.

Consider the following as an outline of a hypothetical AUV survey to illustrate how the mission objectives described above could be resolved.

#### 2.1 Mission 1 Detect

The AUV will explore an area of the seabed (Fig. 4 a) of which it has limited if any a priori knowledge. It will keep a constant altitude above the seabed optimal for maximum areal
2.2 Mission 2 Verify

The AUV re-plans its mission to navigate along a routine to visit all the waypoints. To save energy, the path planning will involve use of Traveling Salesman Planning (TSP) algorithms to have the new path as short as possible (Krogstad and Wiig 2014; Tsiogkas et al. 2014). At every target it activates relevant sensors (UHI, magnetometer, O2-optode etc.) for measuring and sampling (Fig. 4 d). This data is then processed to determine if the targets should be regarded as possible OIOs. The autonomy layer then decides if it should reject the targets and continue with its original mission, or revisit again for full data acquisition (Fig. 4 e).

2.3 Mission 3 Record

Targets determined to be OIOs are revisited and recorded with all relevant sensors to secure optimal data sets (Fig. 4 f). The AUV will plan survey lines with spacing and altitude appropriate for the sensors that are activated (e.g. ensure at least 60 percent image overlap for photogrammetry). In addition, the AUV must apply computer vision and machine learning algorithms to sensor data in real time to ensure that the area of interest has been covered completely, and to decide when the operation is finished (Giguere et al. 2009).

3 Autonomous detection and recognition of wrecks

Detecting and classifying features in imagery are nontrivial and complex problems. Image segmentation using computer vision and machine learning is a research field given much attention in the last decades, and is currently seeing many breakthroughs—especially within deep learning and artificial neural networking. However, as time and computing power are limited resources for AUVs, simpler algorithms would be preferable for on-board calculations. Imagery produced by acoustic sensors is monochrome, and in principle shows the intensity of echoes for each pixel that represents a specific location on the seabed. In archaeological applications, to recognize features in such imagery as potential OIOs would entail comparison of morphological qualities of the features with an onboard knowledge representation (library) of shapes likely to be found on wreck sites. This approach using learned classifiers for feature or object recognition has been successfully pursued by using Automated Target Recognition algorithms in research on Mine Counter Measures (Petillot et al. 2010; Groen et al. 2010). While this method could probably successfully detect and classify some features as wrecks, a problem would be that the method is inherently biased towards what is already known and therefore less likely to recognize sites that are disintegrated, decomposed or otherwise scattered in an unprecedented (un-modelled) pattern. Wreck site formation processes are very complex, chiefly determined by the characteristics of the ship, the events causing its deposition on the seabed (how it wrecked), the environment of the wreck site and the time it has spent on the seabed (assuming it has remained undisturbed). Mackelroy’s (1978) classic model treats the site formation process almost like a cybernetic system with the ship as input, and loss of integrity and materials as conditional outputs depending on a number of ‘extracting filters’ and ‘scrambling devices’. While this model may seem a bit positivistic today, it nevertheless accounts for the factors influencing a site formation process and describes the variations from structurally intact wrecks like the Vasa, to examples like the Kønnekrabben where disintegration and deposition of materials on the seabed happened over a relatively long time and the traces left on the seabed were spread over several hundreds of meters. It can be argued that in deeper waters, wreck site formation processes are more coherent, as a wreck once it is deposited on the seabed is less likely to be mechanically disturbed (Church 2014). However, even

![Fig. 3. Tripartite mission plan for an archaeological survey.](image-url)
though intact hull structures could presumably be modelled as variations of some shared qualities regarding shape and size, any typical morphological characteristics would eventually be broken down by biology, chemistry, gravity and time (Bjordal et al. 2011). The recognition of wreck sites as they appear in sonar imagery is therefore often a heuristic undertaking were the archaeologist will perceive features in the imagery based on his understanding of the technology (Quinn et al. 2005), and in the context of knowledge of the sea bed terrain (e.g. aided by additional sensors as described by Sakellariou et al. (2007)), empirical experience of probable or possible wrecking processes (Muckelroy 1978), and of course the prevailing currents and other known or assumed environmental conditions in the area.

An alternative approach could be to look for what stands out as different or unusual on the seabed (Girdhar and Dudek 2014). By simply stating that a feature is different from what has been perceived so far, and therefore interesting, this approach sheds the problems of morphological ambiguity discussed above. There would be no need for archaeological knowledge representation and wreck site modeling in mission 1 (the analysis of acoustic data), as the AUV would generate a target list based on its experiences made in the local environment.
This way of shifting the allocation of a problem from the deliberate high-level end of the control architecture towards the more reactive, low-level end could also probably make it easier to adjust and fine tune algorithms as less abstractions and semantic representations are involved.

While this approach will reduce the number of false negatives, it is very likely to include many false positives. Recording would be a very energy and time consuming part of such missions, and to avoid wasting resources on what we can expect to be a high number of uninteresting features, we introduce a mission 2 for verification of targets. While the initial target list in mission 1 was selected to encompass every possible OOI, the purpose of mission 2 is to reduce the final number of false positives. This is done by navigating over all targets found in mission 1 for an inspection with multiple sensors activated. While the morphological variations of wreck sites are almost unlimited, the material composition of the remains of shipwrecks would be easier to delimit. Iron anchors, cannons, and chains are some typical objects that can be found on many wreck sites. An AUV equipped with a magnetometer (e.g. Hugin HUS) has a Honeywell HMR 2300 magnetometer could register magnetic signals near a shipwreck with such objects present. Underwater Hyperspectral Imagers are optical sensors that can record the spectral signature of the seabed with centimeter resolution (Johnsen 2013). The UHI detects light in the spectral range 380-800 nm, with a resolution of 1 nm (Ludvigsen et al. 2014). If the AUV carries a library describing the spectral signatures of materials typically present at wreck sites, it could look for matches or close similarities in the sensor data. Methods in sensor fusion can be used to calculate probabilities with many uncertainties involved - see for instance Wu (2002). This means that signals from sensors that acting alone would give very unreliable indications of e.g. a potential wreck site, in combination with each other could yield estimations with higher degrees of confidence. For instance, a magnetometer could register a magnetic anomaly that together with UHI detection of pigments typical for bricks, would indicate a probable wreck site. Targets found in mission 1 that remain unsupported by sensor data from mission 2 will not be considered possible OOIs. By reducing the number of targets to be fully documented in mission 3, a considerable amount of time and energy is saved.

Marine archaeology, as most marine sciences, have used robotics and utilized the technological development both in sensors and platforms to gain access to areas normally not accessible by diving methods. However, the potential for interdisciplinary benefits in the application of robotics has so far largely remained unexplored as a methodologically significant choice by archaeologists as end users. Rather, robots and sensors have been seen as extensions or replacements/proxies for human presence and observation (for some notable exceptions see Bingham and Foley et al. 2010 and Allotta et al. 2015). When archaeologists inspect a wreck site with an ROV, common for surveys beyond diving range, focus will predominantly be on the visual data acquired by cameras, what the archaeologist sitting next to the ROV-pilot can see, and what can be recognized and classified. This is no wonder, as state-of-the-art HD-cameras now can produce fantastic imagery exceeding the perceptive constraints of the human eye. It seems that the primacy of vision, as described by Jonathan Adams (2013), has been transferred to these new methods, and while the diver is no longer situated at the site – with all the cognitive processes that follows – the operation could be seen as an adaptation of traditional marine archaeological diver based practice.

On land the implementation of computer vision and machine learning in archaeological knowledge production has met resistance (Bennett et al. 2014). It is different under water. The operational constraints of ultra-deep or ice covered waters make autonomous operations the only way to access certain areas. Even if some will argue that the methods deployed are ill-suited or inappropriate, the alternative would be nothing at all. This doesn’t mean that the critiques of these methods are irrelevant, but the outcome of such a discourse would have less practical consequences. The abilities to consider and fruitfully deliberate archaeology will only be developed if archaeologists engage with the inner workings of robotic autonomy. It requires an understanding of how intelligent autonomy frameworks function, and it of course requires an understanding of archaeological praxis – both critical to current methods, and aware of trade-offs in transferring a traditionally humanistic praxis to machines.

4 Conclusion and future work

This paper has proposed a strategy to implement archaeological mission objectives as input to the design of autonomous control systems for AUVs. By dividing the missions into tasks that the AUV can perform with behaviours within given parameters, the abstract goals are moved from the higher deliberative layer to the middle coordination layer and finally can be executed in the lower control layer with commands and direct reactions to sensor data determining actions.

It has been demonstrated that SAS in terms of resolution and coverage allows detection of relatively indistinct wreck sites at considerable distances (Ødegård et al. 2013). Future work at the Centre for Autonomous Marine Operations and Systems (AMOS) will look at how on-board SAS image analysis can best be applied to detect wrecks with a focus on avoiding false negatives. UHI-technology is still a novel tool with a huge potential for the marine sciences, but has already been used to investigate wreck sites with good results (Ludvigsen et al. 2014). Ongoing work at AMOS will build a library of spectral signatures for typical materials found at wreck sites. UHI data from wreck sites will be used together with this library to develop methods for aided detection and classification.

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