Long-duration Autonomy for Open Ocean Exploration: Preliminary Results & Challenges

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I. Introduction

The warming of the planet driven by anthropogenic causes, with most of the heat and the CO_2 driven into in our oceans, has resulted in substantial loss of sea-ice in the Arctic region [1], representing a profound threat to biodiversity. Monitoring rapid environmental changes is of extreme urgency and to do so by moving towards sustainable and persistent ocean observation. With the emphasis of the ocean as the primary sink for greenhouse gases, ocean science and the study of the changing climate has become critical to understanding our planet. Much has been made, however, of the lack of data and the need to analyze oceanographic phenomenon at scales not approachable with current observation tools and methodology, which often rely on traditional ship-based methods. These observations methods are not continuous, cause substantial release of CO_2, disturb the boundary layer significantly, are not cost-effective and therefore limited in scaling across space and time. We believe reliance on such methods should be reduced by augmentation with recent innovations in Robotics and Artificial Intelligence (AI) research which have enabled autonomous systems to make continuous measurements in support of observing dynamic processes in the harshest conditions [2].

Meso-scale ($> 50km^2$) observations as a stepping stone for understanding the impact of the changing climate on the worlds oceans have been hampered by sub-sampling, either because sensors and platforms are constrained by proximity to ship or shore, by lagrangian motion, by sensor payload or limited onboard energy [3], [4]. With the onset of robust marine robotic platforms including unmanned aerial vehicles (UAVs), ASVs and autonomous underwater vehicles (AUVs), the transition to systematic robotic observations has become reachable [2]. Meso-scale variability can best be observed with mobile platforms which can sample with a range of sensors for chlorophyll, biomass, temperature, salinity, vertical current structure, sea surface height, turbulence etc. Such observations need not only to be synoptic, but also need to be coordinated across space and time to observe the same patch of the ocean co-temporally (Fig. 1). The science driven objectives for such a capability are to observe the deep-ocean, as well as complex phenomenon such as gyres and eddies, blooms, anoxic zones, fronts and bio-geochemical plumes of natural and anthropogenic nature. All of these phenomenon require observing the water column at different spatio-temporal scales, from minutes to weeks and from a few square km to tens and hundreds of square km. To date, we already have extensive operational capability with multiple networked heterogenous assets for upper water-exploration driven by a scientific hypothesis [5], [6], [7], [8]. Our objective is to extend this effort with data driven operations that require the need for predictive information from shore-side models. This in-turn can help autonomous robots in the near future, to make careful choices in *when, where and how* to achieve its goals. Decision-support

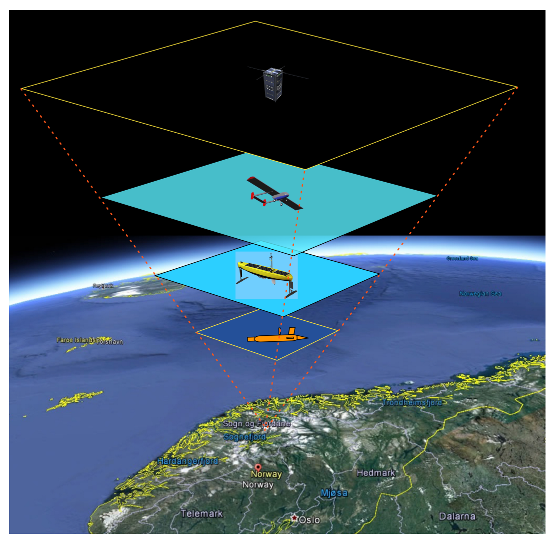


Fig. 1: A vision for coordinated observations that encompasses space, aerial, surface and underwater platforms being designed and implemented in Norway and Portugal.

Fig. 2: The AutoNaut ASV operating in Trondheimsfjord.

systems on ship and shore, will provide oceanographers real-time data with the capability of command/control of assets in the field, which is currently not possible. Conversely, the needs of the oceanographers can be met by controlling aerial platforms to opportunistically direct its sensors and resources towards their specific objectives at the appropriate windows of time.

In so doing, our intention is to leverage these efforts towards building a **persistent observational capability** by embedding an advanced AI decision-engine. We have chosen to focus on the commercially available AutoNaut [9] (Fig. 2), a green-energy wave-propulsion driven autonomous surface vehicle (ASV) which relies on solar energy for powering its scientific payload. In large part this choice is driven by its low cost, simplicity of operation, innovative propulsion system and use in a university environment. In the process we have designed from the bottom up, new control automation which will embed machine intelligence for information driven exploration. It will be goal-driven, fed by shore-based ocean and sea-ice models while simultaneously evaluating and reacting to perceived risks in the short and medium term especially in targeting ice-infested northern waters.

II. Previous efforts

Past efforts in ASV autonomy have typically focused on demonstrations, path planning and collision-avoidance [10], [11] as a ”measure of risk”. Equally, with the exception of CARACaS [12], none have showcased work in deliberative control. Critically, none have been driven by ocean model data or considered operational risks related to ASV mission success and scientific data gathering. Risk assessment methods generally evolved postwar and are mainly focused on event based risk modeling, such as fault and event trees. Current methods continue to rely on such an approach and are mostly applied during the design phase of system development and not for operations. [13], [14] and [15] present risk and reliability issues related to autonomous underwater vehicles (AUVs). A general challenge,however, is to include system-wide couplings and updated risk information during operation, which has led to the development of dynamic risk assessments and modeling, for example [16], [17], [18]. Such dynamic methods reassess risk and update event probabilities when new information becomes available, either using Bayesian approaches or physical reliability models [19], but these have so far not been implemented for autonomous systems' decision making. During autonomous system operations, such as with the AutoNaut , risk control needs to support decision-making both for the human operator and by the autonomous system itself [20]. A proactive and dynamic approach to risk reduction and risk control should be integrated with decision making algorithms, which means advancing from the existing reactive safety systems that a vehicle is pre-programmed to activate when a safety constraint is violated. This is also the overall objective of supervisory risk control, which is an emerging research area combining expertises in control systems design and risk management. The aim is to create autonomous systems with enhanced intelligence and automatic high-level decision-making through implementation of risk management capabilities [21]. Automated Planning/Execution is therefore a ripe technology for implementation of supervisory risk control, requiring risk models to be transformed into suitable knowledge representation methods for online operational risk evaluation.

III. Methods

We present the field-tested methods that we adopt in order to solve open challenges that must be handled to achieve robust autonomy. Moreover, design choices and system architecture solutions are motivated and proved with results.

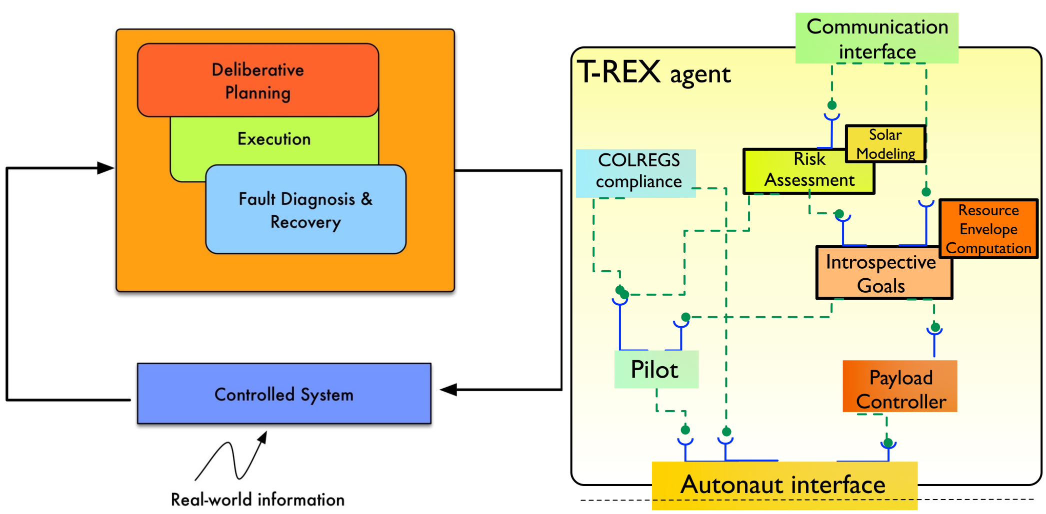
Automated Planning & Execution

Planning is an abstraction layer above control-theoretic methods and generates plans for desired outcomes or intents rather than specific detailed formulations. In doing so, it synthesizes a sequence of actions transforming the initial state of a robot into a state that satisfies predefined goals [22]. By incremental decomposition of these goals and de-conflicting of task outcomes and ensuring appropriate resource usage, automated planning and execution of those plans, lifts the command/control of robotic platforms towards human comprehension and validation (Fig. 3a). Acquiring the model of the environment and actions is done through a Knowledge Engineering (KE) process that transforms the real world into a symbolic representation such that the model is consistent, accurate, complete and operational [23]. As the model is an abstraction of the real-world conditions, generated plans might not accurately reflect the real (and changing) environment and hence KE is a challenging task with the emergent need for support tools. The field has had a range of successful applications especially in space exploration [24], [25], Urban Traffic Control [26] as well as in marine robotics and exploration [27], [7], [28]. The advantage of Automated Planning is that plans aim for longer-term goals and are usually much more complex than policies specified by traditional control systems. Plan synthesis in real-world environments, especially those in the dynamic and harsh confines of the open ocean, is challenging and required to be done *continuously* typically by employing the sense, plan and act paradigm [29]. The Teleo-Reactive EXecutive (T-REX) [27] in particular is the only deliberative control framework in operational oceanography [30], [8], [7], [31] and engineering [32], [7] (Fig. 3b). In addition, it's underlying planning engine, $\texttt{EUROPA}_2$ [24] has had with a significant NASA [33], [25] legacy, and will form the foundation on which to advance the science of autonomy. While mission specific deliberative control has been demonstrated in the open sea [32], [8], [7], [28], [31], sustained and continuous autonomous control is still an open challenge and even more so, under dynamic conditions experienced by an ASV, where communication with shore would be sporadic over expensive satellite links. Generated plans would likely be invalid during sustained exploration, relying on shore-based operators for support with new or modified goals, is untenable and the system has to be self aware, robust to operational failures and risks, and therefore in a position to generate its own goals.

Our goal is to change a platform designed for human-in-the-loop control for surface observations, to a vehicle which can take high level human intent, and computationally break it down into actionable tasks, while being critically aware of operational risks related to shallow bathymetry, surface traffic, low solar irradiance or overly calm waters (Fig. 4). To do so, we will generate novel ways to encode models onboard, imbibe low-bandwidth ocean model predicts, enable *in-situ* data interpretation and enforce the ability to monitor itself to circumvent future failures included in risk models by tasking itself with new goals without human intervention.

Design Choices & System Architecture

Our research is rooted in the idea that, unlike common robotic platforms, this system is less constrained by energy limitation with respect to both propulsion and payload. Among the possible design solutions, the proposed architecture complies with the



(a) Continuous deliberation drives the robotic agent in the real-world, that in turn provides feedback, acquired through sensors, to support the deliberation process.

(b) T-REX agent high-level block diagram.

Fig. 3: Continuous closed-loop Automated Planning and Execution is at the core of the deliberation technique on the AutoNaut.

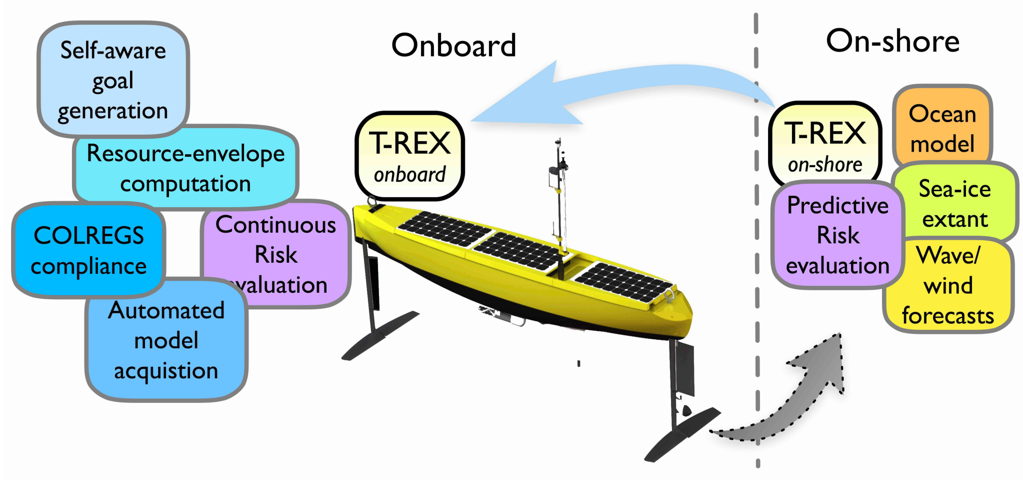


Fig. 4: Elements interacting with `T-REX`, a deliberate planning/scheduling framework, as a means to alleviate risk for sustained operations of a persistent ASV.

self-powering nature that characterizes the vehicle and ensures long-duration field missions without physical human intervention.

The developed architecture, publicly documented in [34], equips the ASV with autonomous navigation control and communication capabilities, integrated in separated units that we describe in detail. The implementation of reliable navigation control and communication constitutes the first step towards more ambitious missions that will involve automated operations of the wide-ranging scientific payload the vehicle is equipped with, to serve as an *in-situ* data provider for oceanographers and biologists.

In our field-tested concept, a three-layered system subdivision allocates responsibilities to three separate computational units (Fig. 5). The layered design provides the vehicle a high degree of redundancy and robustness, essential features required by missions spanning weeks and months. *Level 1* subsystem monitors the health status of the overall system and implements fallback behaviors [35]. It also manages energy harvesting from solar panels, energy storage in the onboard battery bank, and distributes power to various components of the system by controlling dedicated solid state relays. Working as a state machine, it is able to take complete control of the vehicle whenever a failure occurs and to execute user-defined fallback maneuvers. *Level 2* equips the platform with more sophisticated navigation control and collision avoidance capabilities. Depending on the scenario, that may require the execution of an evasive maneuver, a dedicated algorithm computes and dispatches rudder angles and (if necessary) thruster actuation to *Level 1*, which communicates with the motor and servo.

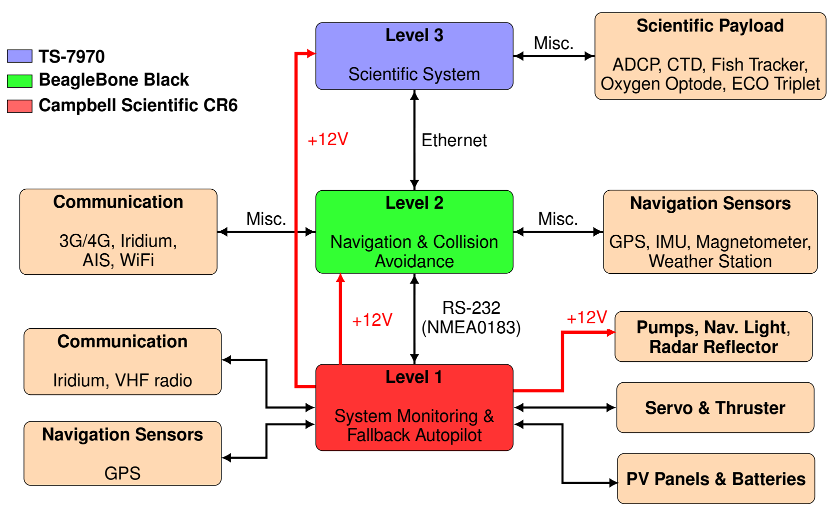


Fig. 5: System Architecture for the `AutoNaut`.

Finally, *Level 3* controls the vehicle's scientific payload depending on the mission profile and manages data storage. Data from the sensors are then compressed and sent to *Level 2* and subsequently transferred to the operators over Internet or WiFi.

Our system is based on an open-source software framework for autonomous vehicles (`LSTS` Toolchain [36]), that provides a unified Graphical User Interface allowing the operator to both upload new mission plans to the vehicle and manually control it from shore. Mission plans are sent to *Level 2*, that analyses their goals, and generates a feasible trajectory together with desired references for the speed and course controllers. A 4G/LTE modem instantiates a bi-directional communication over internet, that makes the operator able to both send plans to the vehicle, but also to receive all the messages needed to have a full real-time stream of the mission in the laptop graphical interface. Manual control of the vehicle can be achieved by directly communicating to *Level 1*, through VHF radios. Over VHF the operator is able to: monitor the overall state of the system (battery charge, power consumed, power produced by solar panels, etc), power on/off sensors and units, apply a desired fallback behaviour and pilot the vehicle rudder and thruster. Unlike 4G/LTE, whose coverage can be poor or non existent in many areas, VHF-based communication does not depend on network coverage and its transmission range can reach several tens of kilometers. Moreover, operations in open ocean are supported by Iridium Satellite communication, that allows both the vehicle to send housekeeping messages to the operators, but also the operators to update mission plans and hardware/software configurations.

IV. Experimental Results

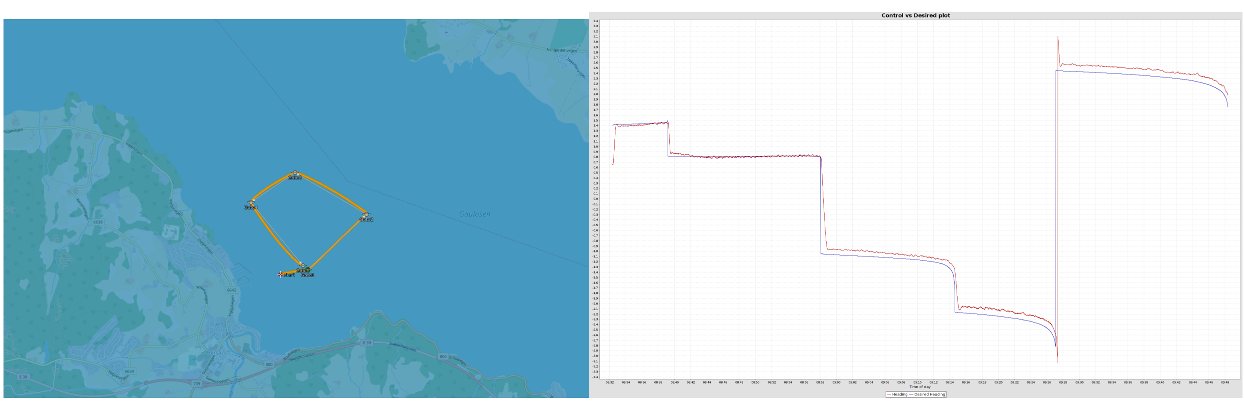
The proposed architecture has been tested on the field in fjords near Trondheim, Norway. Before implementing sophisticated high-level decision-making algorithms, the essential navigation capabilities and communication methods have to be tested extensively; the results below are therefore preliminary in nature. The unique propulsion system and the wave related dynamics of the vehicle make navigation and control challenging research tasks to be addressed. The *Level 2* unit implements high-level control of both the speed and the course of the vehicle. A course-keeping autopilot constantly computes the desired course needed to the vehicle to reach the desired way point from its current location. Measurements of speed and course are provided by a GPS-compass chosen primarily because of its ability to provide a course and heading measurement at low speeds.

Fig. 6a shows the pattern covered by the vehicle while trying to reach five waypoints in sequence. The high-level navigation law used for this maneuver is *pure pursuit*, meaning that the course-keeping autopilot only tries to minimize the error between the desired and the actual course. More sophisticated techniques have also been tested, i.e. *line-of-sight (LOS)* and *integral line-of-sight(ILOS)*, where the controller also tries to minimize the cross-track error. For a slow-moving vehicle, whose turning dynamics is slow and highly related to speed and waves/wind direction, pure pursuit is enough to reach the target destination. However, the performances may quickly degrade due to high winds and currents. Fig. 6b shows desired and measured heading. When switching to one waypoint to the next, a cross-track error is accumulated during the turning maneuver. The controller used does not try to reduce it, leading to a constant error that can be reduced with an integral action.

V. Principal Challenges

Persistent monitoring capabilities involve several challenges principally to deal with a high degree of robustness and endurance in hardware and software. The control of robotic systems and the communication with them are challenging tasks due to the variation and unpredictability of the environments. These amount to the following:

Environmental factors The propulsive power of the `AutoNaut` is heavily dependent on surface waves. Goal driven intent for scientific measurements will require careful balancing of value of information with the ability to be at the *right place at*



(a) Sequence of five waypoints in `AutoNaut` field trials for accurate navigation and geo-location.

(b) Desired and measured course for the vehicle.

Fig. 6: `AutoNaut` navigation and control field trials in Trondheimsfjord.

the right time. We propose to mitigate this by evaluating 'risk' online using an ensemble of factors related to sea surface weather, sea-ice conditions, solar irradiance (to drive the scientific payload) and dynamic prioritization of goals.

Balancing goal-driven opportunism with intent Data and sample collection will be driven not only by the form and content of the information collected, but the urgency of returning that data (samples) to shore. Water samplers onboard the `AutoNaut` for example can only be considered 'fresh' enough for analysis within specific time windows. The conundrum of *exploration vs. exploitation* will then need to be worked out within the context of the value of information by trading (for instance) the cost of gathering and enabling sample return versus exploring 'interesting' regions elsewhere.

Balancing operational risks with remote intent While the vehicle is in-situ and has a well-defined situational awareness of its environment, the onboard goal-driven autonomy has to trade operational risk in the 'here and now' with the desire and intent shaped by humans on shore who might not have full situational awareness or worse, issue command directives in error.

Communication challenges Deciding *what and when* to transmit collected data to shore will be a significant challenge especially in northern latitudes where satellite communication coverage is sparse.

In order to improve mission flexibility, constrained by communication gaps, and ease operational executions, the `AutoNaut` needs to be equipped *robust autonomy*. As an example, the vehicle needs to be able to autonomously detect and characterize faults related to hardware or software as also to exogenous (and unforeseen) events. Once anomalous events are identified and classified, a communication routine will need to be instantiated. The `AutoNaut` is equipped with internal algorithms (in *Level 1*) capable of diagnosing undesired outcomes and report them to shore. Working as a state machine at low level, this processing unit can take control of the vehicle and adopt a user-define behaviour (i.e. course-keeping autopilot) whenever the current circumstance is classified as dangerous.

Put together, our operational domain and the vehicle come together to provide robust solutions to a significant challenge to long-duration autonomous operation, driven by goal-driven decision-and-information theoretic systems. We believe that in taking on this challenge we will be in a position to make significant contributions to the science of autonomy.

VI. Conclusions

Deploying robust and autonomous entities for robotic exploration implies a number of challenges that need to be carefully analyzed and solved. This work discusses and proposes a scientific approach and a technological solution to address the challenges of open ocean exploration. Long duration autonomous operations is a way to study the environment for extended periods of time. For the open ocean surface layer, this may be done today in a more sustainable way without use of fossil fuel. More generally long duration autonomous operations may extend high resolution sampling into remote environments, barely accessible to humans. In this document we motivate the design choices of a platform chosen to address these challenges of monitoring such unstructured environments. Furthermore we motivate our vision with the necessity to tie together several disciplines to provide answers to relevant scientific questions.

VII. Acknowledgements

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