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Autonomous subsea intervention (SEAVENTION) ⋆

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Abstract: This paper presents the main results and latest developments in a 4-year project called autonomous subsea intervention (SEAVENTION). In the project we have developed new methods for autonomous inspection, maintenance and repair (IMR) in subsea oil and gas operations with Unmanned Underwater Vehicles (UUVs). The results are also relevant for offshore wind, aquaculture and other industries. We discuss the trends and status for UUV-based IMR in the oil and gas industry and provide an overview of the state of the art in intervention with UUVs. We also present a 3-level taxonomy for UUV autonomy: mission-level, task-level and vehicle-level. To achieve robust 6D underwater pose estimation of objects for UUV intervention, we have developed marker-less approaches with input from 2D and 3D cameras, as well as marker-based approaches with associated uncertainty. We have carried out experiments with varying turbidity to evaluate full 6D pose estimates in challenging conditions. We have also devised a sensor autocalibration method for UUV localization. For intervention, we have developed methods for autonomous underwater grasping and a novel vision-based distance estimator. For high-level task planning, we have evaluated two frameworks for automated planning and acting (AI planning). We have implemented AI planning for subsea inspection scenarios which have been analyzed and formulated in collaboration with the industry partners. One of the frameworks, called T-REX demonstrates a reactive behavior to the dynamic and potentially uncertain nature of subsea operations. We have also presented an architecture for comparing and choosing between mission plans when new mission goals are introduced.

Keywords: Autonomous and remotely operated marine vessels; Intelligence and autonomy in marine systems and operations

1. INTRODUCTION

Underwater infrastructure plays a key role in today's society and includes, e.g., oil and gas installations, aquaculture facilities, underwater cables, etc. Moreover, both, e.g., aquaculture and oil and gas infrastructure are expected be installed in even more exposed areas offshore. Also, renewable energy installations such as offshore wind is alone projected to reach $56.8 billion by 2026 (Nhede, 2021). To optimize asset uptime and ensure proper HSE (Health, Safety and Environment) Unmanned Underwater Vehicles (UUVs) are used for inspection, maintenance and repair (IMR) of offshore infrastructure, and the global underwater robotics market in general is expected to reach $4914 million at a CAGR of 12.5 % from 2018 to 2025 (MarketResearchFuture.com, 2020). Still, most UUVs in IMR operations are piloted by humans or otherwise operating with a limited degree of autonomy. Increased autonomy in UUV operations can improve HSE and efficacy, lower emissions and reduce cost in UUV-based IMR operations (Schjølberg et al., 2016). Methods to achieve such autonomy are the topic of our 4-year project called Autonomous Subsea Intervention (SEAVENTION) and in this paper we summarize the main results and latest developments from the project. The subsea oil and gas industry has been the

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main focus for the SEAVENTION project, but the results are also applicable to IMR operations in other sectors such as offshore wind and aquaculture.

The subsea oil and gas industry has been a long-term user of UUVs for IMR. In particular, Remotely Operated Vehicles (ROVs) have been the standard for IMR. ROVs are tethered and typically have two robot arms for intervention operations such as turning valves, cleaning, etc. Over the recent years, UUVs have been endowed with autonomous capabilities, but these are mainly limited to non-intervention type tasks such as inspection, hovering, follow-pipeline, move from A to B, etc. Intervention operations (e.g., cleaning, turn valves) are mostly remotely piloted by one or more human operators. Thus, the efficiency and success-rate of such operations rely on the operator skills. Hence, factors such as limited visibility and ocean currents can make operations very challenging to perform in a safe and efficient manner. Hence, there is a need for methods for robust perception and intervention to meet these industry challenges.

In this paper we present main results and recent developments on UUV autonomy from the SEAVENTION project ranging from perception and control to automated high-level mission/task planning. We discuss the status and trends in IMR with UUVs in the oil and gas industry and provide an overview of the state of the art on UUV intervention. Moreover, we list IMR use-cases, present a 3-level taxonomy for UUV autonomy, and we summarize our results on marker-based (with associated uncertainty) and marker-less approaches for object detection and localization for UUV intervention. We also present an approach to UUV localization sensor autocalibration. Lastly, we provide an architecture for comparing plans for UUV missions in a planning framework called ROSPlan and compare ROSPlan with a another framework called T-REX.

2. BACKGROUND

2.1 State of the industry

In this section, we provide an overview of how subsea IMR operations with UUVs are typically being performed in the oil and gas industry today and what are the subsea operational concept trends.

The main mode of operation for IMR is that ROVs and ROV pilots are brought by large topside support vessel to the area of subsea installations in need of IMR. The ROVs are tethered and operated by ROV pilots often onboard the surface vessel (typically large ships, see Fig.1). In recent years, remote support of operations with ROV pilots and/or subject matter experts onshore have become more commonplace. E.g., SEAVENTION project partner IKM has demonstrated remote controlled ROV operations over a distance of 11 000 km (IKM Subsea, 2019). Moreover, SEAVENTION partner Oceaneering reports that *ROV remote piloting from shore can increase safety and reduce the environmental footprint of operations, potentially achieving up to 25% reduction in offshore personnel on board (POB) and provide a significant reduction in emissions associated with the work* (Oceaneering, 2021).

A next step beyond today's need for large topside support vessel is to have UUVs that perform IMR on subsea

Fig. 1. Example of ROV support vessel (Ken Doerr, CC BY 2.0 https://creativecommons.org/licenses/by/2.0, via Wikimedia Commons)

Fig. 2. A Merlin Resident ROV with its "garage" from IKM. Image courtesy of IKM.

templates without topside vessels present. In June 2017, the world's first commercial ROV operation with a "work-class" ROV was carried out from IKM Subsea's operation center in Stavanger, Norway (See Fig.2. Even though such "resident" UUVs are still not commonplace in subsea IMR, oil and gas companies such as Equinor are pushing toward such operational capabilities and thus we may see more of it in the future. As an example, Equinor has engaged a company called Saipem to deliver resident UUVs (Saipem, 2019). In addition to resident UUVs designed to operate within limited areas, e.g., close to a subsea template-type of infrastructure, other UUVs are starting to appear, such as the Freedom Autonomous Vehicle from Oceaneering (see Fig. 3) with a survey range of 120 km and offshore trials reported to be in 2021 (Oceaneering, 2022). To support UUVs traveling between subsea assets, companies such as Equinor in cooperation with Blue Logic are testing UUV docking stations with standardized interfaces for UUV charging (BlueLogic, 2019).

In the past, UUVs were divided into mainly two categories; 1) ROVs (tethered, limited operational area, hovering capabilities, typically equipped with two robot arms and a range of inspection and intervention tools) and 2) Autonomous Underwater Vehicles (AUVs). AUVs were often "torpedo shaped", designed for long-range surveys and monitoring missions (e.g., seabed mapping, pipeline inspection) without hovering and intervention capabilities. However, we now see more "hybrid" types of UUVs capable of hovering, intervention, and more long-range survey operations. Such UUVs include, e.g., the Freedom Autonomous Vehicle, Aquanaut by Nauticus Robotics (nauti-

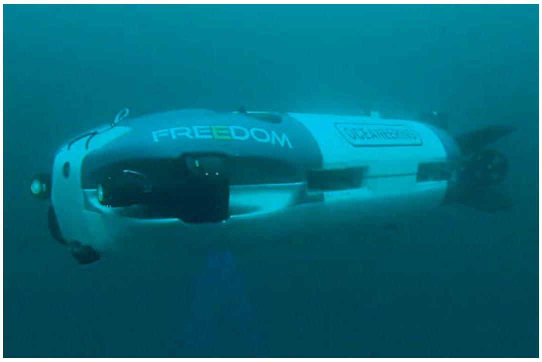

Fig. 3. The Freedom Autonomous Vehicle from Oceaneering. Image courtesy of Oceaneering.

cusrobotics.com) and a snake-like UUV called the Eelume Vehicle (Fig. 4). Some of these can switch between being tethered and un-tethered. Equinor has coined the term "Underwater Intervention Drones" (UIDs) for UUVs that can operate without a tether and perform intervention tasks.

Fig. 4. The Eelume vehicle. Image courtesy of Eelume.

2.2 The state of the art on autonomous intervention

UUVs are to an increasing extent equipped with manipulators for intervention purposes. Such vehicles are referred to as underwater vehicle manipulator systems (UVMS) (Antonelli, 2014). This provides a moving base for the manipulator that strengthens manipulation capabilities and enables more autonomy in intervention operations. Autonomous underwater intervention is relevant in a vast amount of diversified scenarios, from pipelines and operational panels in offshore industry to collecting organisms such as plants and fish. The latter case requires gentle and agile grasp in order to not damage or injure the object of interest (Huang et al., 2020). Such scenarios would require a system with high accuracy and delicate movements which again set the requirement for both hardware and software. A manipulator is a versatile tool with its potential for accessibility and maneuverability, and the flexibility to use a range of end-effector tools and different manipulator assemblies for modular arms. They are used in the oil and gas industry (Schjølberg and Utne, 2015), aquaculture (Bjelland et al., 2015), ocean mapping, environmental monitoring, surveillance, etc. (Simetti, 2020). The high variation in scenarios where manipulators and UVMSs are deployed is met with an equally high variation in available systems. Underwater manipulators vary in the range from small electric manipulators with limited lifting capacity and depth rating to large hydraulic manipulators capable of lifting hundreds of kilos at depths of up to several thousand meters. Manipulators in all sizes vary from simple setups with few to none joints and simple open/close gripper functionalities to more advanced manipulator that may inherit a variety of integrated capabilities, e.g., force feedback, joint position readings, multiple internal controllers and so on (Sivčev et al., 2018).

Autonomous underwater intervention has long been a prominent research topic, with considerable variations of innovative solutions in the research community. One of the first autonomous underwater intervention operations in the oceanic environment was conducted through the SAUVIM project (Marani et al., 2009). Since then, among other projects that targeted autonomous intervention operation we find, e.g., TRIDENT (Simetti et al., 2014), MARIS (Simetti et al., 2018) and DexROV (Gancet et al., 2015). One of the leading projects in autonomous intervention today is the SUONO project (Topini et al., 2021), which aims to develop autonomous systems capable of performing underwater intervention operations such as free-floating manipulation tasks on a subsea panel.

3. USE CASES AND LEVELS OF AUTONOMY

Typical IMR operations subsea which involves the use of UUVs (mostly ROVs) include cleaning, visual inspection, valve operations, hot stab operations, installation/retrieval/replacement of modules and components (e.g., flying leads, jumpers, cables, sensors, meters), electrical faultfinding and hydraulic lead detection, operating hatches, cutting, surveying (e.g., with cameras) and Cathodic Potential (CP) measurements of structures and pipes (Schjølberg et al., 2016).

The above operations are complex and can be broken down to subtasks such as change tool; detect, locate and move to valve; record camera data; operate tool; docking; charging; etc. where the latter is specifically for non-tethered UUVs. IMR operations require UUV capabilities ranging from low-level vehicle control to high-level mission planning. To this end, we propose a 3-level division of autonomous UUV capabilities:

Mission-level: UUV capabilities in terms of planning its own missions fully or partly (in collaborating with a human operator). Such mission planning can include sequencing and coordinating a variety of task-level capabilities to achieve mission goals while taking into account vehicle and environment constraints.

Task-level: Capabilities to carry out single tasks autonomously or through high-level cooperation with a human pilot. Such tasks could include turn valve, inspect gauge, follow-up pipeline, etc.

Vehicle-level: These capabilities include autonomous hovering, collision avoidance, and object detection and localization.

With the above taxonomy, we see from Sec. 1 and 2.1 that today's UUV operations in oil and gas are mostly limited to vehicle-level autonomous capabilities, while for inspection operations (e.g., pipeline following), UUVs show, to some extent, task-level autonomy.

4. ROBUST 6D UNDERWATER POSE ESTIMATION

To achieve reliable autonomous UUV intervention we need robust 6D (6-Degrees of Freedom) pose estimation (vehicle-level autonomous) capabilities. To achieve such pose estimation, we have developed and tested marker-less deep learning (DL) approaches with input from 2D and 3D underwater cameras, as well as marker-based approaches with associated uncertainty with 2D cameras (e.g., with Aruco markers). We have carried out controlled experiments with varying turbidity to evaluate if the proposed systems provide robust 6D pose estimates in challenging conditions. To facilitate the training of machine learning-based perception systems, we have also implemented an approach to collect and automatically annotate underwater 6D pose estimation datasets. In the following, we summarize our efforts on these topics.

Collection and automatic annotation of dataset for 6D pose estimation The performance of 6D localization has significantly improved with the advent of deep learning – especially in terrestrial application. Our research has focused on how 6D DL methods can be adapted to images acquired in the underwater environment while retaining their superior performance. One of the main challenges is that the visual appearance of the same object will vary with the turbidity. The higher turbidity, the more noise and less contrast we will observe in the images. To reliably train such DL networks requires large annotated datasets which can be costly to generate.

One approach which we have developed (and published in Mohammed et al. (2021)), is a way of generating a dataset for 6D localization with automated 6D labeling even under turbid conditions. We created a mockup subsea panel which contained objects such as valves, gauges and fish-tails. A number of Aruco markers were placed around the panel (both above and below the water). Two cameras were rigidly attached to each other, where one camera was located underwater while the other (an underwater 3D camera) was located above water. Since the positions of the Aruco markers in relation to the objects of interest were well calibrated, we could use the Aruco detections above water to annotate the 6D localization of the objects in the underwater camera even under very turbid conditions. The level of water turbidity is varied by adding clay. We measured the water turbidity, by way of attenuation lengths, to be in the range of 8.3m (clear) to 2.2m (turbid).

Deep learning model for 6D pose estimation We also developed and trained a DL pipeline to predict the 6D pose of the annotated objects. Fig. 5 shows the developed DL pipeline. The DL network includes 4 sub-tasks that combined solves the task of object 6D pose estimation. Class and box prediction sub-networks handle detecting objects with 3D data while handling multiple object categories and instances. The processing time for a single frame is 62.5msec or 16 frames per second using a single GPU (GeForce RTX 2080 Ti, 11GB). In Fig. 6 (a), we show the annotated detections (ground truth) overlaid on the intensity image across turbidities. Fig. 6 (b) shows the estimated pose projected on the intensity image.

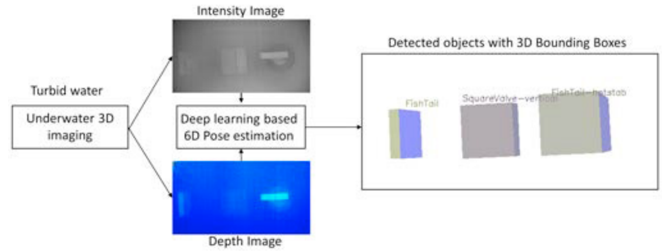

Fig. 5. 6D pose estimation pipeline: The deep learning model takes both intensity and depth image as an input. The network is trained in a single stage to detect and regress the 6D pose under different level of water turbidity.

(a) GT **(b)** Pred. 3D bounding box

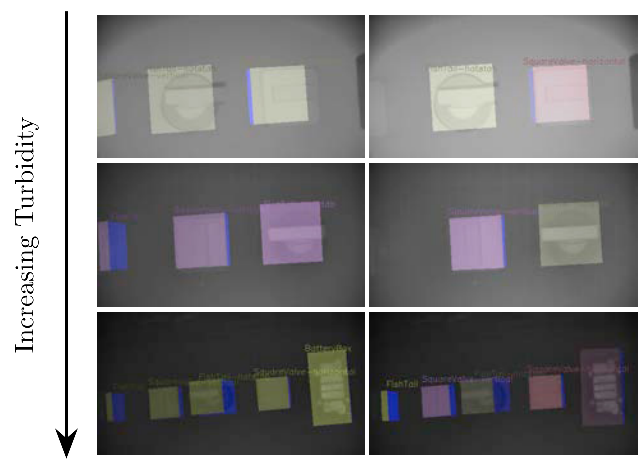

Fig. 6. Qualitative results for detection and pose estimation: Column (a) and (b) shows ground truth and estimated pose projected on the intensity image respectively. The top, middle and last row shows ground truth and predicted pose result for increasing turbidity.

Uncertainty of 6D pose estimation Basing critical autonomous decisions on highly uncertain localization information can potentially lead to catastrophic outcomes that not only risk the success of the autonomous vehicle's mission, but also endanger human lives. As current DL-approaches to pose estimation do not associate an uncertainty with the 6D pose prediction, we have developed methodology for associating 6D predictions with the inherent model and data uncertainty.

Aruco markers are often used as an effective way for autonomous systems to be able to locate themselves in relation to rigid objects. Here we summarize an approach published in Risholm et al. (2021) where we developed a system for 6D estimation of Aruco markers with associated uncertainties in the challenging underwater environment. A state-of-the-art object detection framework (EfficientDet) was adapted to predict the corner locations of Aruco markers, while dropout sampling at inference time is used to estimate the predictive 6-DoF pose uncertainty.

We captured a dataset of Aruco markers in a wide variety of turbidities, with ground truth position of the corner

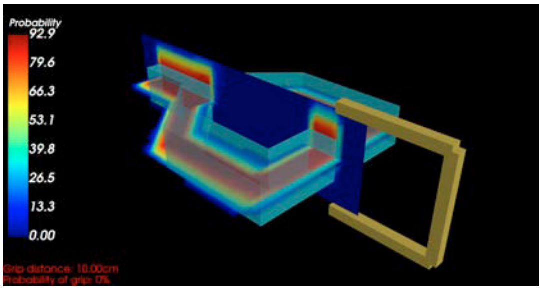

Fig. 7. Gripper in relation to the predicted distribution of the location of the fish-tail handle. As the gripper is moving closer to the handle and closing its grip distance, the probability of having a solid grip will increase according to the uncertainty field.

locations, to train the network to robustly predict the 6D pose. We report translational errors of 2.6cm at low turbidity (8.5m attenuation length) and up to 10.5cm at high turbidities (0.3m attenuation length) while the associated uncertainty (inter-quartile range) ranges from 3.2cm up to 27.9cm. The rotational errors varied from 5.6° to 10.7° with uncertainty of 6.4° to 26.2°. Compared to OpenCV Aruco library with standard detection parameters, we observe that the detection rate falls off rapidly with higher turbidities, while the proposed method provides a detection rate of 100% Risholm et al. (2021).

One direct application of the proposed approach to 6D pose estimation is for autonomous interventions subsea. If an Aruco marker is rigidly placed in relation to a fish-tail handle which an UUV should intervene with, the UUV can automatically position itself and the gripper in relation to the fish-tail. In Fig. 7 we show an example where we have used the pose distribution given by the proposed algorithm to create a probability volume of the location of the fish-tail in relation to the gripper. When the gripper (the yellow model) is closing its grip, we can report the probability of whether it is now gripping the fish-tail. The gripping procedure can be adjusted according to the uncertainty of the pose estimate of the fish-tail. With high uncertainty, the movements can be slower, and the gripper can open up more before closing up the gripper. This will help reduce the risk of damaging the gripper and the fish-tail.

5. AUTOCALIBRATION

This section presents an autocalibration method for localising a vehicle with two or more sensors that we published in Bjerkeng et al. (2019). In this context, the calibration is the problem of finding the relative positions/orientations and time delays between the different sensors used on an UUV. If this calibration is not accurate, then a sensor fusion for e.g. localization will have poor performance. The method, which we have validated with real data from experiments, was first proposed by Furgale et al. (2013), and uses B-splines to represent vehicle trajectories. The calibration is performed by capturing time series data from all the sensors during vehicle motions, then an optimization problem is solved off-line. Our implementation splits the dataset into 1) identication and 2) validation, as in cross-validation. To avoid over-parametrization, one is used during optimization and the other is used to check the result after the optimization has terminated.

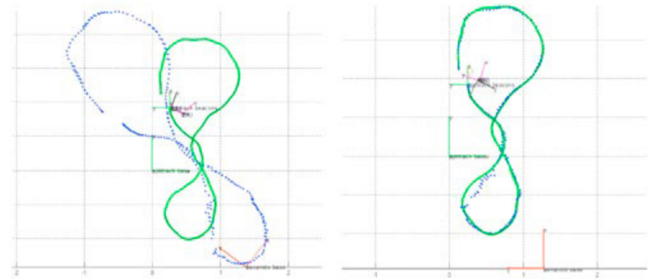

Fig. 8. Vehicle trajectory before and after calibration. Note that on-board sensors and base stations/transponder poses are calibrated at the same time.

The method does not need extra equipment or external references, other than a data series which sufficiently excites all the relevant degrees of freedom. It will calibrate relative poses between on-board and external sensor references, as well as scaling and sensor time-delays. Our main contribution is the integration of cross-validation in the solver. Cross validation enables the user to see if the calibration result is correct, and can detect over-fitting.

The method requires that a user models the bias characteristics of each sensor. Steps building on the cross-validation were taken to automate this step, but no simple solution was found. It was seen that the quality of the calibration result was quite sensitive to bias modeling. If the user has little information about the bias characteristics of e.g. a gyroscope, then this modeling error would be a significant source of error.

6. AUTONOMOUS UNDERWATER GRASPING AND MANIPULATION

Autonomous intervention relies heavily on both software and hardware. An autonomous system requires software that provides intelligent solutions regarding navigation, guidance, perception, pose estimation, grasp position, decision making, and more. In order for this to be possible, its software demands the hardware to provide the necessary sensor information (e.g., joint feedback, sonars, cameras, etc.). However, sensors give additional cost and payload of the system. In the work presented in this section, we have therefore focused on intelligent software solutions with minimal additional sensors to provide intelligent systems capable of autonomous functionalities at low cost. In (Haugaløkken et al., 2020) we developed a grasping procedure to grasp known objects using monocular vision with a small UVMS. This work followed the work presented in Skaldebø et al. (2019), where we presented a large image dataset of the object of interest, an automatic labeling procedure of the image dataset, training of the detection model and the object detection procedure. One of the main goals was to provide an effective solution for object retrieval mission for a small, low cost UVMS. Moreover, in these works we also designed a navigation, guidance, and control system for the vehicle to maintain a desired position relative to an object detected through monocular vision and object detection using the vehicle's camera. The system proceeded to grasp the object while maintaining the desired position relative to the object and thus provided a task-level autonomous capability. The system was validated in experimental testing with a UVMS consisting of a BlueROV2 vehicle and a SeaArm manipulator. Moreover, in the experimental validation of the system, the gripper was closed manually, making it a semi-autonomous operation. The experiments were conducted in the Marine Cybernetics Laboratory (MC-lab) pool at NTNU, where two out of a total of seven experimental trials were successful. A test was considered successful if the object was grasped. The five unsuccessful experiments failed when the manipulator stopped, either due to singularities or hitting the vehicle because of occlusion. Thus, occlusion avoidance presented itself as the greatest challenge.

Presented with the challenges from (Haugaløkken et al., 2020) we developed a new system in (Skaldebø et al., 2022) with a new manipulator, a SeaArm-2. This work presented fixed-base autonomous underwater grasping of objects using a monocular camera integrated in the manipulator end-effector as the main sensor. In addition, the work presented a novel distance estimator enabling relative distance estimation between object and manipulator without prior knowledge of the object size or shape using only a monocular camera. The distance estimator combines state-of-the-art object detector and tracker systems for 2D footage with the inherent information of end-effector translation through joint manipulation. In this way the system estimated the size and shape of objects of unknown size, e.g. underwater infrastructure, fish, plastic waste, etc., and further calculated the relative distance based on the estimated sizes. The distance estimator was validated in experimental testing using an experimental procedure consisting of the modes 1) Search, 2) Estimate distance, 3) Grasp and 4) Retrieve. In the grasp mode, the system also estimates preferred gripping angle in order to best grasp the object. This is especially relevant for elongated objects , where it might be impossible to grasp it lengthwise. The experiments were performed in the MC-lab pool with the SeaArm-2 fixed at the bottom of the pool. The manipulator was able to find, estimate relative distance, grasp and retrieve the relevant object in 12 out of 12 trials. In the experimental validation the distance estimator found the relative distance between the object and manipulator with a root mean square error of 9.21 mm.

7. AUTOMATED TASK PLANNING AND ACTING

While typically, UUVs operation rely either on teleoperation or pre-scripted missions, neither of those approaches are tractable when mission objectives or environments are continuously and unpredictably evolving. Instead the UUV needs to autonomously determine what needs to be done by balancing its (human) user-specified objectives, and the current context the UUV is in. Goal-directed high level control (Ghallab et al., 2016) provide such capability: it aims at making the *acting* control loop of the robot being informed by *automated planning*.

Acting is the process to identify and execute, at any point, the best course of actions to execute a command, given its “contract” (e.g. maximum duration, allowed battery budget, successful completion, ...). This process is tightly embedded within the UUV control loop and therefore focuses primarily on the current actions at hand rather than how they contribute to the long term objective of the operation. Those long term objectives are handled by *planning*: it is an inference process that given 1) a model of possible actions, 2) the current state of the actor – in our case the UUV – within the world, and 3) a set of desired objectives; identifies a sequence of actions that should allow the actor to fulfil its objective. The idea is then to give this plan to the *acting* pare of the UUV.

Integrating *acting* in *planning* is far from trivial as both processes affect each other but yet both have conflicting temporal constraints and scope. Many different designs have been introduced to address this tension but our work, in following sections, focused on two specific frameworks:

ROSPlan (Cashmore et al., 2015) is a popular framework for integrating AI Planning tools with a Robot Operating System (ROS)-enabled system (Quigley et al., 2009). It supports planners that use the Planning Domain Definition Language (PDDL) standard (Fox and Long, 2003). The *planner* is seen as a service which, when called upon, will search for a complete plan for the mission. This *plan* is then given to the *action* loop that will call upon the *planner* only if the observed world state has deviated from what was planned. The clear functional separation of *planning* and *acting* simplifies the architectural design which greatly contributed to its popularity and the impressively wide range of planning frameworks it supports. Still seeing the planner as a service also means that whenever the system *plans*, the *acting* loop can only wait.

T-REX (Py et al., 2010) on the other hand aims for tighter integration of *planning* and *acting*. It allow multiple *planning* and *acting* decision loops – called *reactors* – to be composed by having a well-defined model of ownership of *state variable* (each state variable is maintained by one and only one reactor, that declare it *internal*, while others can only receive *observation* updates and request future *goal* values to this variable) along with requiring every *reactor* planning to be suspended at a specified “tick” rate in order for each to identify their *internal* state for other reactors to consume. This blurs the line between *planning* and *acting* as each reactor do both concurrently, but at the cost of a much more complex integration of any planning framework. Therefore, as far as we know, the only planner it fully supports is the EUROPA planning framework (Frank and Jónsson, 2003).

7.1 Automated task replanning with ROSPlan

In this section, we contribute a previously unpublished strategy to address the problem of automated replanning for UUV missions in dynamically changing underwater environments. We explicitly explored enhancements in the replanning approach during the execution of inspection, maintenance and repair (IMR) tasks as new goals can emerge during IMR mission. We present a method that analyzes the trade-off between continuing with the current plan and deferring new goals until later, versus performing a full replanning that incorporates the new goal. Our strategy also considers the urgency of the goals to be achieved, alongside the resources available to the mission. Implementation and testing of this approach was done within the ROSplan framework. Simulated action components are set up with code which includes the name and duration of each action. Thus, we can test planning for a UUV without having to engage a physics-based simulator in the testing process.

The proposed architecture of our planning system is shown in Fig. 9. An operator provides a description of the world model the UUV is operating in and of a set of mission goals to be achieved. These are stored in a Knowledge Base. An initial problem is generated by a Problem Generator and fed to a planner which produces an initial UUV mission plan. The plan is then executed and a module called Dispatcher updates the Knowledge Base when the actions of the UUV are achieved or failed. If the operator decides to add new goals while the aforementioned thread of the initial plan is executed, a new parallel thread handles the updated problem and generates a new plan. We have developed and inserted a Replanning Node that evaluates the revised plan, and if it meets the criteria of the human operator, it then triggers a new dispatch. Hence, our approach allows the parallel evaluation of candidate new plans that adapt to goals that emerge during the mission execution. This is without interrupting the current mission and while respecting the overall mission resource constraints, alongside possible priorities of certain actions in the original plan.

The features of the Replanning Node sum up to:

- It prompts the operator to add possible new goals or other facts if necessary.
- It allows the operator to select which action or clusters of actions need to have been completed before launching a new plan dispatch.
- It allows to update the knowledge base with the new goals and accordingly facilitates new plans that also consider the operator-defined priorities.
- It offers functionality that cancels the current plan and updates the dispatcher with the new plan based on the updated knowledge base and metrics of urgency of the mission actions.

It is noted that while replanning iterations take place, the ongoing mission as commanded by ROSPlan may continue.

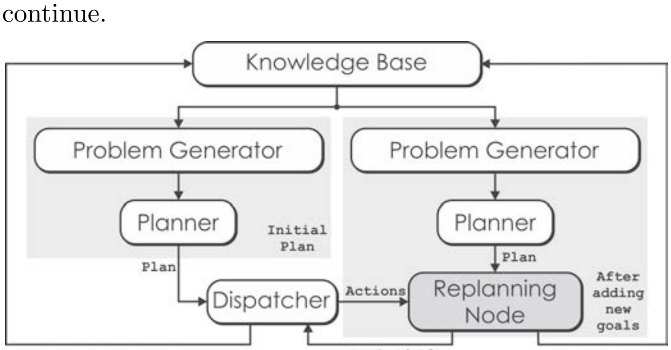

Fig. 9. The Replanning Node in the proposed architecture of the planning system.

7.2 Comparison of AI Planning frameworks

In Xue and Lekkas (2020) we conducted a comparison between T-REX and ROSPlan (without the extensions in Sec. 7.1), in the context of a subsea scenario formulated in collaboration with Oceaneering, considering the design and capabilities of their Freedom Autonomous Vehicle. Compared to past efforts, where mission planning pertained mostly to path planning tasks, such as dynamic waypoint (re)planning, we considered a more detailed scenario in terms of possible states, tasks and actions, including, for instance, inspection of certain components (valves, pipes), doing self-diagnosis before leaving the docking station, installing tools depending on the tasks, and so on.

The subsea scenario in Xue and Lekkas (2020) took into account several of the novel features of the Freedom vehicle, such as the existence of an underwater warehouse, where the vehicle can switch tools, and a docking station, where it can charge and communicate with a shore control centre. The mission itself included the following steps: First perform a pipeline inspection, then an inspection of Valves No. 1 and 3, located on Panel 1, and finally intervention of Valves No. 3 and 4, located on Panel 2. To accomplish the mission, numerous actions had to be planned, including the vehicle performing self-diagnosis, undocking, moving from one location to another, approaching a component, performing inspection and/or intervention, and others. In addition, we introduced an unplanned event in order to test the replanning capability of each framework; When the vehicle inspects Valve No.2 it finds it is not in the right setting and therefore intervention is required. It should be noted that only the action planning aspect of the problem was dealt with, without simulating the complete guidance, navigation and control system of the vehicle.

Our results showed that ROSPlan planned for 12 unnecessary actions compared to T-REX (56 vs. 44 actions) to complete the task. The 12 additional actions were not implemented (since ROSPlan updated the plan in the next working cycle), but T-REX avoided planning them altogether, hence demonstrating a more reactive and computationally efficient behavior. To summarize further, it can also be advantageous to use ROSPlan for planning and execution UUV tasks with less stringent requirements to reactive behaviors, as, e.g., ROSPlan has a rather large user group, supports different types of planners and is well documented.

8. CONCLUSION AND FUTURE WORK

We have presented results ranging from vehicle-level autonomy (e.g., perception, autocalibration) to mission-level autonomy (task planning). We have also focused on robustness as, e.g., perception methods tested in varying turbidity. These aspects will be important in enabling fully autonomous UUV missions in the cases where close (human) operator involvement is not possible or desirable. Further work will focus on further increasing robustness of methods and integrating capabilities into autonomous missions with a suitable level of operator involvement.

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