Integrated MCM missions using heterogeneous fleets of AUVs

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***Abstract*—The capability and cost effectiveness that unmanned underwater vehicles (UUVs) bring to underwater survey, target detection and identification operations has been widely demonstrated and accepted in recent years. However, these operations still rely mainly on pre-planned missions and require a high level of expert human interaction both at the planning and data analysis stages. In this paper, we present an integrated mission approach using heterogeneous fleets of UUVs that provides a series of performance improvements over state-ofthe- art solutions. The approach is formed by a combination of novel automatic target recognition techniques, distributed knowledge representation, and algorithms for autonomous inmission decision making. This results in an increase tempo of operation as well as an improvement in the pertinence of the gathered data whilst reducing the need for expert human input. The benefits of the approach are demonstrated in real in-water trials where vehicles have different capabilities and collaborate to perform a mine hunting clearance process for a user-defined area of the seabed.**

I. INTRODUCTION

Gathering timely and high quality data in the sub-sea environment is a key challenge of the 21st century. This data is required for marine science; in the offshore and the military domains to monitor changes in the environment. More and more applications are now taking place in deep water where human divers cannot operate. In this environment, traditional techniques for data gathering based on ships or remotely operated vehicles do not provide the required speed, sensor resolution or navigation accuracy. Unmanned Underwater Vehicles (UUVs) have now become a real alternative to replace traditional means of sub-sea exploration. In the last decades, they have demonstrated their capability and cost effectiveness for underwater operations such as survey, inspection and light intervention [3]. Their mission planning is relatively primitive and very rarely adaptive to developing faults on the platform, or on-line interpretation of the sensor data. Most of todays sub-sea exploration missions can be broken down into the simple primitives of search, classify identify, mapping & intervention (SCMI). In this paper, an approach for sub-sea survey, target identification and intervention operations that improves on current state-of-the-art systems is presented. It is applied to a typical mine countermeasures scenario, which involves the survey of an area, the detection of potential targets and their final identification. This scenario could be applied to many other applications in the marine science, offshore and archaeology domains. The approach is based on multiple autonomous vehicles collaborating to achieve their objectives. The approach uses a high level of semantic interaction with the operator for describing the mission goals and domain. A nonexpert operator is able to specify high level goals (search, classify, identify) and the vehicles can jointly plan and execute these goals. Once the mission goals have been specified, a knowledge based framework finds the match between the high level goals requirements and the capabilities of the vehicles. A planner is then used to plan and coordinate the actions of the vehicles. The planner uses embedded knowledge on each platform to activate the capability required by a specific action. This planner can adapt the actions of the platforms based on on-line sensor data analysis or information exchange with another vehicle. This paper is organized as follows: In section II, the overall architecture of the system is described. In section III, the approach for automatic target recognition is presented. The mechanisms for knowledge distribution across services and platforms is presented in section IV. The autonomous decision making algorithm is presented in section V. Finally results obtained during a set of loch trials is presented in section VI and the improvements against state of the art is evaluated.

II. MULTI-VEHICLE SERVICE-ORIENTED ARCHITECTURE

We propose a solution to the search-classify-mapintervention (SCMI) of a seabed area using heterogeneous fleets of UUVs. At the heart of the system are three key modules:

- An unmanned vehicle knowledge base framework to represent the mission objectives, the vehicles capabilities, and the current state of the world (from the vehicle(s) perspective). It enables reasoning and planning based on the current internal (capabilities & current goals) and external state (information gathered from external sensors) of the vehicle(s). Because of the limitation of acoustic communication, an efficient communication protocol allows this framework to prioritise and share mission-critical information across the vehicle collective.
- An autonomous decision making module used to plan the actions of each vehicle. This mission planning module

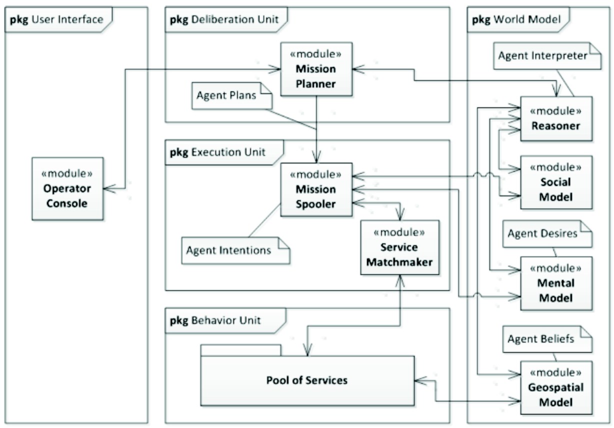

Fig. 1. Service-oriented architecture of the system showing the interaction of the adaptive mission planner with the user interface, the world model and the services available in the platform.

Detection	Classification	Identification	Neutralisation
High-level Operator Interface	Low Resolution ATR	Hovering	Low cost and disposable
Fast area survey		High Resolution ATR	Acoustic and Video-based target homing
Accurate Navigation		Accurate Position Reacquisition	Hovering / Docking?
Goal-based planner	Sidescan ATR	FWRD-looking acoustic camera	Downward Camera
High-Res Sidescan	World Model	DVL-aided navigation	LBL-aided navigation
DVL-aided navigation	Planner	World Model	World Model
	Acoustic Comms	Planner	Planner
		Acoustic Comms	Acoustic Comms

Fig. 2. Matching of the SCMI phases of the mine hunting process with the service capabilities provided by the three different types of platforms used in the approach.

is goal-based and high level. The user specifies high level goals such as search, classify, map, intervene and each vehicle automatically generates the specific detailed plan for each of these goals which is best adapted to its current capabilities and its knowledge of the environment. This plan is adapted on-line during the mission as new information becomes available. This is done without any operator intervention.

- Automatic target detection (ATR) and identification algorithms. This algorithms are critical to the performance of the system as they provide the essential link between data and information. In our case the algorithms analyse sonar data and try to identify potential targets of interest in the data. This information is integrated into the knowledge based system and used by the planner to plan and adapt each vehicle mission plan.

A summary of the architecture is presented in Fig. 1. In order to demonstrate the effectiveness of this architecture for high level goal-based planning of multiple assets, the following mine hunting scenario was used: a specific area of seabed is designated by an operator. This area needs to be cleared from mines by a set of vehicles equipped with a different range of sensors and services. Targets needs to be detected by a survey-type vehicle and then identified and reacquired by another vehicle. A third-type vehicle can then be used for intervention. Each vehicle can implement a set of services that are matched against the mission specified by the user. The matching between the SCMI phases and the service capabilities provided by the different types of platforms is presented in Fig. 2.

III. Automatic Target Recognition

In the context of this paper, ATR is a key service as the adaptive mission planning will only be able to work effectively if the semantic information provided by the ATR is sufficiently accurate. In practice, this means that the false alarm rate of the ATR must be sufficiently low (a few per mission) to enable meaningful replanning. Target detection underwater is traditionally performed using sonar due the good propagation properties of acoustic wave in water. Automated approaches are required to tackle the large amount of data produced by modern platforms using high resolution (cm) sensors and help the operators in its decisionmaking. ATR in sonar imagery turns out to be a difficult task due to the large variability of the appearance of sonar images as well as the high level of noise usually present in the images. Many methods have been proposed to tackle this problem, from model based [7], [17] to learning techniques [5], [6]. These approaches suffer from poor computational efficiency, making real-time on-board operation on low-power hardware difficult. This is even more important with the extremely large amount of data produced by emerging sonar systems such as SAS (Synthetic Aperture Sonar) or video-rate acoustics such as the DIDSON, BlueView and Gemini Sonars. They also exhibit a relatively high false alarm rate, which makes autonomous mission adaptation for inspection and neutralisation impossible. We propose a new method for object detection in sonar imagery based on the Viola and Jones boosted classifiers cascade [15]. Unlike most previously proposed approaches based on a model of the target, our methods is based on in-situ learning of the target responses and the local clutter. Learning the clutter is vitally important in complex terrains to reduce the false alarm rates while maintaining high detection accuracy. Coarse-to-fine search is a natural approach to achieve computational efficiency. Cascade models, first popularised by Viola and Jones [19] explicitly use a sequence of classifiers with increasing complexity to distinguish target from nontarget image patches. This approach has attracted our attention because of its ability to process images at video rate, yet achieving better performances than the best published results in the sonar ATR field. Cascade classifiers rapidly focus the attention of the algorithm on the few areas of interest, away from the background, and concentrate the processing on these areas. This is achieved by rejecting as many negatives as possible at the earliest stage possible.

Fig. 3 describes the detection cascade structure and shows a subset of the haar features used in classification. An input patch is classified as a target only if it progresses through all the stages. More difficult tasks, requiring more complex

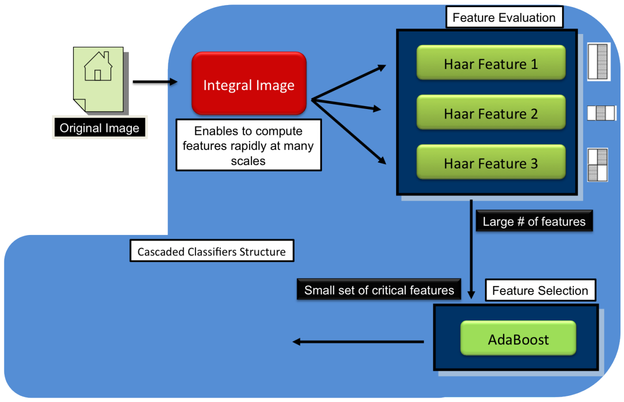

Fig. 3. Matching of the SCMI phases of the mine hunting process with the service capabilities provided by the three different types of platforms used in the approach.

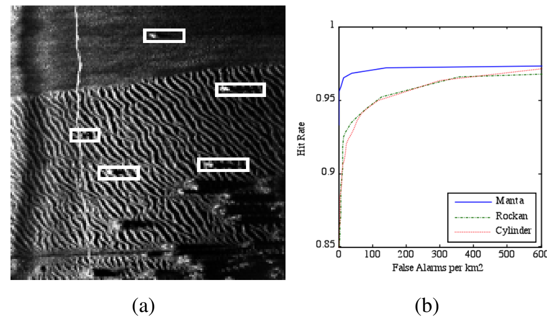

Fig. 4. Examples of images containing cylindrical, truncated cone and wedge-like objects corresponding to the three classical mine types. The targets are simulated and placed in a real sonar image containing real seabed. The simulation of the targets takes into account the sonar beam pattern and the angle of view of the target.

features or algorithms are tackled by classifiers appearing in the later stages, where only a few patches of the image are remaining. The classifiers used at each stage of the cascade are trained using AdaBoost. The key insight is that smaller and therefore more efficient AdaBoost classifiers can be constructed to detect almost all positive examples (e.g. 99.9%) while rejecting a large proportion of the negative samples (e.g. 50%). For our application, we need to develop ATR for two sensors: side scan sonar for large scale survey and detection and identification and forward looking sonar for identification and intervention. The application of the algorithm described above to these two sensors and the results obtained on real data acquired during the Loch Earn experiments are described in the following two sections.

A. Automatic Target Recognition in Sidescan sonar and SAS

The algorithm proposed here was tested on real and simulated data. The simulated data uses an augmented reality using an object simulator and sonar renderer model to place ground truth objects into real sonar data [2]. The real data consists of a set of 450 targets acquired using the MUSCLE SAS Sonar from the NATO Undersea Research Centre in La Spezia as well as data collected during our loch trials. In each case, half of the target data was used for training and half for testing. Some example of background were also used for training (around 10%). Examples of images produced by the augmented reality framework and the corresponding ROC curves for different target models are shown in Fig. 4. Results obtained on the SAS datasets are shown in Fig. 5.

The data gathered in Loch Earn is in many ways more challenging. First the sonar resolution is limited compared to SAS data; second, there is a limited amount of training data available. Two targets were placed on the seabed, the real target and a decoy (see Fig. 11). The data for training was gathered during 3 missions where around 50 views of the targets and seabed were recorded. The target was subsequently moved to another area for testing. Examples of training data samples of the target are shown in Fig. 6.

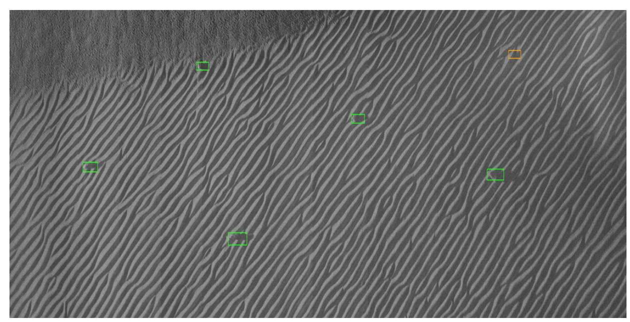

Fig. 5. Examples of images containing cylindrical, truncated cone and wedge-like objects corresponding to the three classical mine types. The targets are real targets from the MUSCLE SAS Sonar Dataset provided by DTSL. The green squares represent real detections and the orange squares false alarms.

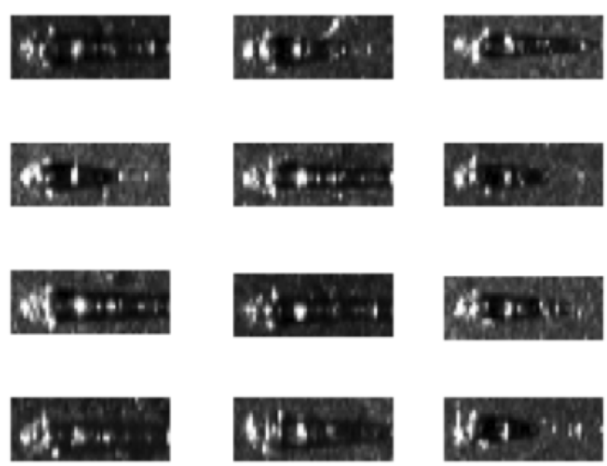

Fig. 6. Sample snippets of truncated cone target used for training over sidescan data.

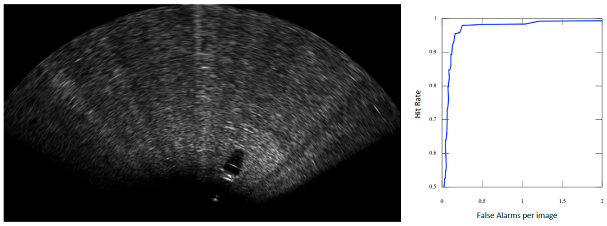

Fig. 7. Example of XY Gemini sonar image including one view of Manta target (left). ROC curve for the detection algorithm.(right)

The resulting algorithm was then repeatedly used to detect and identify the target of interest during the subsequent missions. Result were very encouraging, with an average of 2/3 false alarms per mission. The area covered was around 0.1 Nautical square miles which translates to false alarm rate of 20/30 false alarms per Nautical square miles. This number is compatible with operational constraints and would only require a few close inspections during a standard mission.

B. ATR in Forward looking sonar

The same algorithm has been used in forward looking sonar. The data consisted of forward looking sonar image sequences gathered at 1Hz with a hover capable vehicle. The images were gathered in polar coordinates and the classifier was trained in this coordinate system. The visualisation was done in Cartesian coordinates for clarity. The dataset was split into two section, one part was used for training and the other part for testing. The identification rate was 96% with 1 false alarm every 4 frames. The detector is capable of working at video rate as each image is processed in less than 40ms on a 1.6GHz intel Atom processor. It is therefore compatible with most state of the art video rate forward looking sonar such as the Blueview and the Gemini sonar. This detector could be integrated into a tracking system to improve identification performances and reduce the false alarm rate. Examples of data gathered by the Gemini sonar for identification and the ROC curve of the algorithm are displayed in Fig. 7.

IV. Distributed Knowledge Representation

As a mission progress, new information is gathered by agents (targets position for ATR) and needs to be shared with other agents effectively. This information must also be placed in context using the domain knowledge (Mine detection application). This is best achieved by standardizing knowledge storage and transfer. In terms of communication middleware, different message transfer protocols have been proposed to share information [16]. They enable embedded agents to read data from sensors, to write commands to actuators, and to configure devices on the fly. Blackboard approaches [8] are vulnerable to bottle-necking at the server as the ASCII messages can generate considerable parsing overheads. On the other hand, distributed broadcasting approaches can flood the communication network. Neither of these approaches standardise the semantic content of the information transferred.

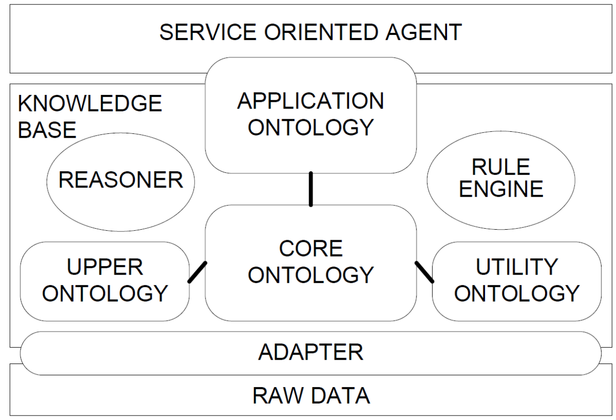

Fig. 8. Knowledge Base using Core and Application ontologies supported by Upper and Utility ontologies. Generation of instances from raw data is performed by the Adapter. The handling of knowledge is done by the Reasoner, Rule Engine and the Service-Oriented Agent.

The Joint Architecture for Unmanned Systems (JAUS) proposes a common set of concept and services, generic across the robotics domain (land, air, underwater). These concepts and services can make the link between the data observed; the information extracted from this data; and the domain knowledge (what to do with the data?, what does it mean for the mission?) . This is not currently done in JAUS. We present a novel semantic world model framework to combine sensor data with domain knowledge [12], based on JAUS. Our representation of the knowledge is based on ontologies. They allow different embedded agents to communicate shared concepts whilst keeping sole responsibility and awareness of the services that they provide. The representation of the knowledge base is displayed in Fig. 8.

In the context of Mine detection, it means that different combinations of acting/sensing/processing can provide the same conceptual information and therefore the same capability. This can be used by the planner to coordinate multiple vehicles at higher level (what an not how). The same approach can be used by the human operator to describe mission goals that can be understood by the planner and transcribed into services. When working with a collective of vehicles, information and goals must be shared. Each vehicle has its own world model storing the current state of the world and vehicle (including the vehicle goals and intentions). The vehicles communicate using a subscription and priority-based information distribution protocol. This protocol takes into account the low-bandwidth of acoustic communications. Platforms only subscribe to information that they can use.

V. Autonomous Decision Making

The challenges for providing autonomous mission planning for UUVs were clearly stated by [18], [13]. Approaches previously validated in Space have been able to provide adaptive planning capabilities to oceanographers for maximising the science return of UUV missions [14]. Using learning techniques for the identification of features [4] and deliberative reactors for the concurrent integration of execution and planning, live sensor data can be analysed during mission to adapt the control of the platform in order to measure episodic phenomenon. Other approaches have made use of behaviour-based controllers that generate Pareto-optimal and satisfying behaviours to control the direction and velocity parameters of the host platform [1]. Our approach for autonomous decision making is motivated by the need of a service-oriented architecture for multiple assets, a portable and extensible solution, a dynamic and uncertain environment, and the requirement to maximise operability during mission. We propose a novel approach for adaptive mission planning for UUVs operating in a dynamic and uncertain discoverable mission environment [11]. We assume that the information provided by the knowledge base is fully observable to the planner, i.e. the uncertainty arising from sensor limitations is handled by the agents processing lower-level data, e.g. ATR. We also assume that the mission environment is dynamic and uncertain, i.e. external events may occur and actions do not always perform as expected. Under these assumptions, our approach implements a Bayesian paradigm for prediction, measurement, and correction inside a sequential decision-theoretic planning Markov decision process framework. Based on a continuous reassessment of the status of the mission environment, our approach provides a decision making loop capable of adapting mission plans. Instead of solving a plan from initial state to goals like in classical AI planning, it maintains a window of actions that it is believed can be performed from the current state in order to improve a given utility function. In order to develop a full decision making loop, this approach implements a timeline-based continuous iteration of observation, orientation, planning, and execution stages. We look at the cumulative payoff over a fixed window length. We adopt the value iteration model to implement the search policy, finding the best policy using classical state-space search. The combination of a finite approach with classical search provides computational efficiency: by keeping track of the requirements and expected effects of the actions planned ahead, we are able to forecast the impact of sensed events in the precomputed plan and, if necessary, react in advance. This reaction can be greedy or lazy. The greedy approach recalculates the plan as soon as the changes have been detected. Thus, it provides an optimal approach. Under a lazy behaviour, adaptation is delayed: planning is only performed at the end of the current window of execution. Thus, it provides a pseudo-optimal solution. Our implementation is able to handle temporal planning with durable actions, metric planning, opportunistic planning and dynamic planning. Using the Plan Proximity metric presented in [10], the approach was evaluated in simulation under a static scenario and a partially known dynamic scenario. The comparison results showed a high degree of similarity between our approach and the human driven adaptation. We have applied this approach to control the decision making process of the UUVs. Under this scenario, platforms are considered self-interested benevolent agents, able to react to the new knowledge provided by other vehicles when their capabilities match the needs of the mission. The collision of task allocations is unlikely and only possible with vehicles sharing similar capabilities. This approach optimizes the management of heterogeneous assets and resources by coupling resource capabilities and mission requirements in real time. It also provides a higher level interaction with the operator than current approaches. It is able to provide fast dynamic response to sensed events. It is suitable technique for long term deployment, where the initial goals of the mission are not fully explicit at the beginning and can change over time.

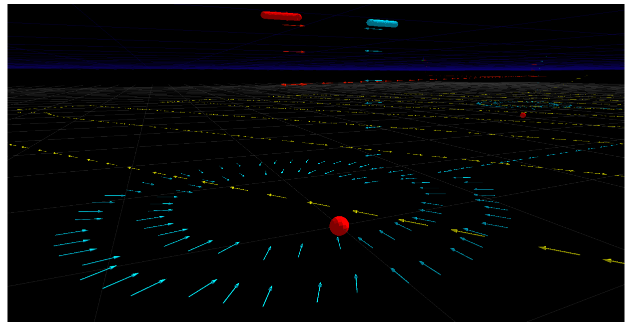

Fig. 9. An example of the high-fidelity simulator: the yellow vehicle performs a survey, the blue vehicle performs a spiral inspection of possible targets identified by the survey, the red vehicle is the intervention vehicle that goes to the targets confirmed by the inspection vehicle.

VI. Results and Evaluation

The full system was evaluated in simulation using hardware in the loop simulation and during real trials in Loch Earn over a period of 3 weeks. The simulation was mainly used as a development tool to validate the autonomous planning module and to verify integration with the real hardware. The main objective of the evaluation was to show improvements against the state of the art using the performance metrics previously described.

An area of approximately 300m by 300m was defined for inspection.

A. Simulation

The simulation environment used here is based on the Robotic Operating System (ROS) environment developed by Willow Garage. Our AUVs and their software modules are all using ROS for information exchange and Rviz is used for visualisation. The simulation environment is connecting to the vehicles software modules and therefore it is the same code that is running in the simulation and on the vehicle. The only part that is simulated is the sensor processing part. We do have access to sonar simulators [9] but they were not fully integrated into the simulation environment. We therefore simulated the output of the ATR to validate the rest of the system. We used a acoustic communication simulator to simulate the information exchange between vehicles. An image of the simulation environment is shown in Fig. 9.

Fig. 10. Platforms: REMUS 100 AUV, Nessie 5 AUV, and Nessie 4 AUV.

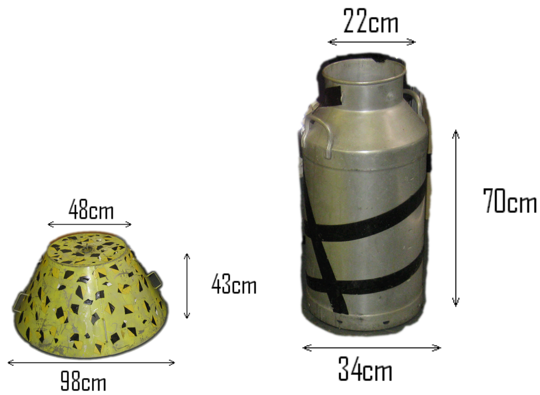

Fig. 11. Targets: truncated cone object and milk churn object deployed in the area of operations. These targets have similar dimensions and shape as well known types of classical sea mines.

B. Integrated Field Trials

The performance of the system was evaluated on the Ocean Systems Laboratory platforms (see Fig. 10) in a set of integrated in-water field trial demonstration days at Loch Earn, Scotland (56o23:10N,4o12:00W). Initially, the plan was to use the 3 platforms but only the first two (Remus 100 and NessieV) were eventually used due to hardware problems with one vehicle.

The area contains clutter on the seabed and several man-made objects, such as sunken rowing boats, anchors and other features such as sand ripples, submerged tree branches and rocks of different sizes.

Two targets were deployed in the area: a truncated-cone object (see Fig. 11, left) and a cylindrical milk churn (see Fig. 11, right). These targets have similar dimensions and shape as well known types of classical sea mines. A high level goal was assigned to platform collective: survey, classify and map this area. The latter stage (intervention) was not included. The mission was deemed complete when every possible target in the area had been identified and mapped accurately. The various phases were assigned to the two available platforms based on their capabilities:

- REMUS 100 AUV was assigned as a platform Type A for Detection and Classification phases.
- Nessie V AUV was a platform Type B for Identification. For communication, all vehicles were equipped with a WHOI micro modem. The two Nessie vehicles were also enhanced with the WHOI PSK coprocessor. This enabled high data rates for up to 2000bytes/15s.

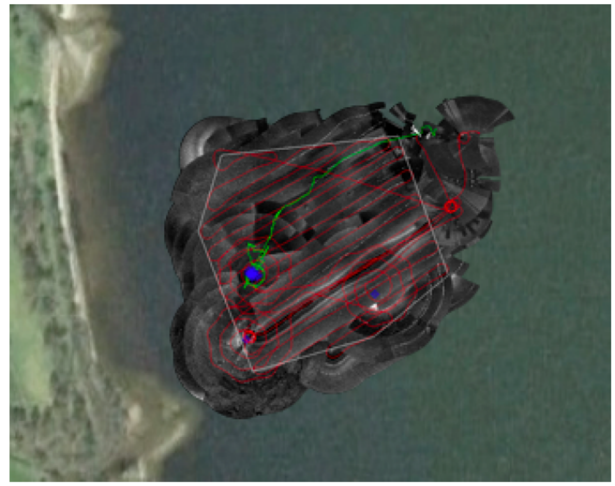

Fig. 12. Mission results from our approach. The area identified by the operator is described by the white polygon. The REMUS 100 AUV track is red and the Nessie V track is green. The hits from the ATR module are shown in blue.

For navigation, all platforms were equipped with navigation systems aided by DVL sensors and a network of LBL transponders.

C. The baseline mission

A series of standard mine hunting missions were performed using only the REMUS 100 AUV. In these missions, a survey lawn-mower pattern was manually scripted providing a full reconnaissance with the sidescan sensor of the designated area. The vehicle was recovered and, after the data was analysed by the operator, a reacquisition daisy pattern was programmed to collect high resolution data over the identified mine like objects.

D. Proposed approach

The proposed approach used two vehicles, the same REMUS 100, equipped with a guest PC/104 1.4GHz payload computer where the services were installed and the hover capable Nessie V vehicle. The two vehicles started their respective missions at the same time and REMUS first performed an initial survey of the zone as REMUS is the only vehicle capable of performing this service. The survey was not preprogrammed by the operator but calculated on-line by the adaptive mission planning module. The ATR module was running live and the vehicle was constantly identifying potential mine like objects. Once the survey was complete, the REMUS vehicle performed a closer inspection of the potential targets using a spiral motion around the target to maximise the number of viewpoints at different angles and ranges on the targets. The potential targets where then ranked by order of priority and Nessie V was used to perform the identification of the most likely target. It is important to note that Nessie V could have performed part of the secondary inspection of the targets and indeed this was done in simulation. However, it was not done during the final trials due to time constraints.

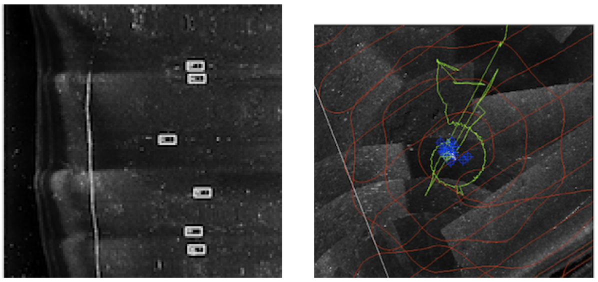

Fig. 13. Series of target detections of the embedded ATR over sidescan data (left) while performing the octagon pattern with the REMUS 100 AUV over the truncated cone target (right).

Fig. 12 shows the results of the collaborative mission on the same area as the initial baseline mission. The reacquisition pattern used enables many hits on the target by the ATR system which enables to quickly disambiguate the false alarms from the real target as demonstrated in Fig. reacquisition.

VII. Conclusion

By removing the operator from the decision making loop, we have shown that greater autonomy than current approaches can be achieved. We have provided a solution that is robust, mature and reproducible in simulation and in a real environment. This, in time, will increase the operators trust in on-board mission planning. By allowing a description of mission in what and not on how-to, the required operator training is reduced and the need for specific knowledge of each manufacturers platform is removed. We have shown that we have increased the mission tempo, providing an approximate 50% reduction in overall mission time from deployment to recovery.

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