ENABLING AUTONOMOUS MINE COUNTERMEASURES FOR THE NATO ALLIANCE

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Abstract: *As many more nations actively transition their mine countermeasures (MCM) capability towards autonomous systems, the NATO Centre for Maritime Research and Experimentation (CMRE) continues to research the utilisation of robotics in the minefield to deliver doctrinally relevant autonomy and on-board intelligence with a view to deliver a NATO capability.*
This review paper will present an overview of the CMRE approach to autonomous mine countermeasures. In particular, this paper will highlight the development of specific enabling technologies regarding sensors, automatic target recognition, autonomy, and in situ planning and evaluation.
These specialised and multi-disciplinary activities are brought together into a system-of-systems approach, which will enable future war fighting capability to adapt to mission specifics and environmental conditions. With a system-of-systems concept come additional particularities and difficulties such as passing target location and its accuracy from one vehicle to another, collaborative autonomy, interoperability and the performance evaluation of a set of heterogeneous vehicles.

Keywords: *NATO, Mine countermeasures, autonomy, robotics, automatic target recognition, synthetic aperture sonar, planning and evaluation, interoperability, target location accuracy.*

1. INTRODUCTION

The Centre for Maritime Research and Experimentation (CMRE) is working to transform the way mine countermeasures are conducted from a post-Cold War approach that focuses on post-operations clearance using surface ships, to a quickly deployable, autonomous system that is scalable, cost effective, and minimizes risk to personnel. Recently, work in the Autonomous Naval Mine Countermeasures group (ANMCM) at the Centre has focused on using AUVs for mine hunting, including developing techniques for handling the large data rates associated with modern high-resolution sonar and developing AUV systems that make decisions based on data that is gathered *in situ*. Now, the Centre's emphasis is expanding from using AUVs in mine hunting to using AUVs in mine identification, developing a network of collaborating heterogeneous vehicles and continued development of novel sensors. This strategy is one that is adopted by many nations and CMRE is committed to supporting these efforts; the Centre's advantage is the ability to rapidly prototype and test new algorithms, concepts and systems at sea, work with nations to develop NATO interoperability and standards and exploit the vast amount of at sea data acquired in a variety of environments

This paper will give an overview of the program of work undertaken within the ANMCM group. CMRE is advocating for multi-phase system-of-systems MCM missions comprising multiple heterogeneous unmanned systems. One such operational example is the Italian Mine hunting Exercise (MINEX) 2018 as shown in Figure 1. However, in such a system-of-system (SOS) MCM scenario, the accuracy on the location of each of the detected targets will naturally affect subsequent phases of a system-of-systems MCM missions, and the problem needs to be addressed from a SOS point of view. The CMRE fleet of vehicles currently comprises:

- the **MUSCLE**, a 21" Bluefin vehicle equipped with a Thales, UK synthetic aperture sonar which focuses mainly on wide area survey and provides a detection and classification capability,
- the Black Collaborative Autonomy Testbed (**Black CAT**) equipped with a forward look 900kHz Blueview sonar, a 2.25 MHZ Blueview multibeam echo-sounder and an optical camera, mainly utilised to test collaborative behaviours, reacquisition of a target and gathering additional information on target,
- the Bi-modal Identification Or Neutralisation DemOnstor (**BIONDO**), a SPARUS vehicle equipped with an ARIS camera, which is employed for acoustic identification and to simulate the behaviours of a neutralisation vehicle.

Each vehicle is equipped with different system adapted to carry out a particular phase or set of tasks with a typical mine hunting scenario; however, the fundamental enabling technologies remain the same:

- the development of on board perception which includes for example on board sonar image processing, automatic target recognition, and target clustering,
- the implementation of *in situ* performance evaluation based on the data, outputs from the ATR and target clustering,
- the increase in vehicle capability to make decisions and to collaborate with our systems.

Additionally, CMRE is building a novel low frequency synthetic aperture sonar concept to tackle the problem of buried targets and difficult environments with a particularly high false alarm rate.

The remainder of the paper is organised as follows: section 2 will present the work related to on board perception, in particular related to the CMRE MUSCLE and the exploitation of the synthetic aperture sonar images produced in real-time on board the vehicle; section 3 will explore the development of in situ performance evaluation, while section 4 will describe the autonomy and the collaborative framework which brings all the aspects of modern mine hunting together. Section 5 will briefly introduce the low frequency sonar to complete the program overview. Section 6 will conclude and offer some thoughts on the evolving CMRE program of work and the transfer knowledge to nations.

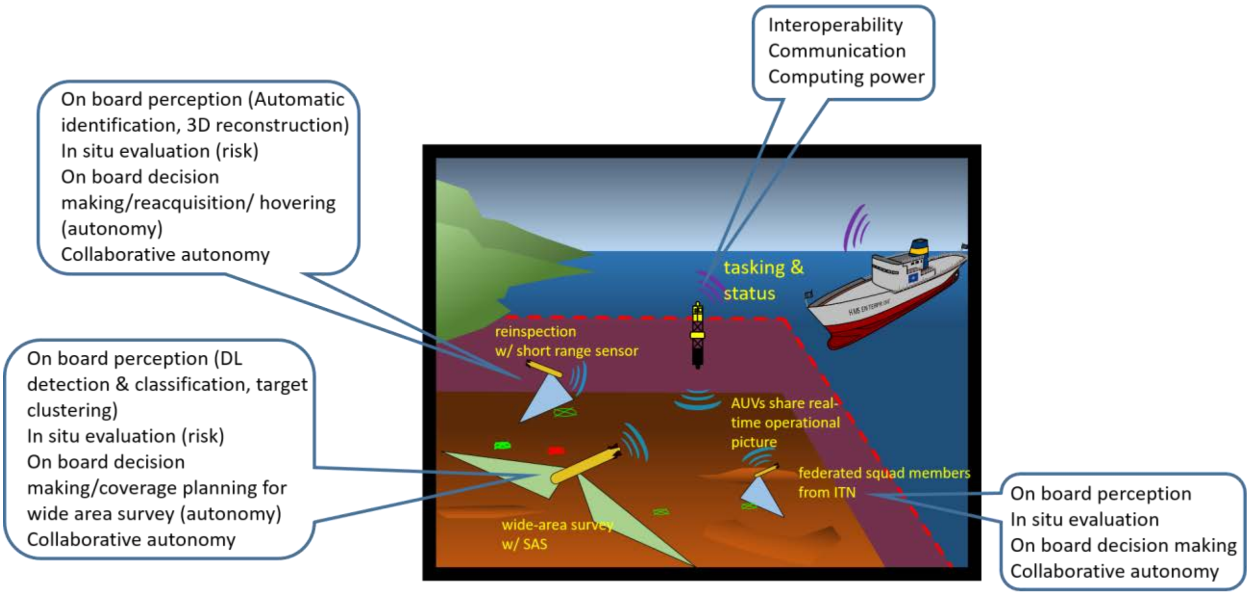

Fig.1: CMRE ANMCM program of work overview shown in an operational view utilised during Italian MINEX 2018.

2. ON BOARD PERCEPTION

2.1. Automatic target recognition

For several years, automatic target recognition research at CMRE has focused on the use of convolutional neural networks (CNNs) [1]. This vision led to CMRE being the first in the underwater MCM community to pursue such an approach [2], which has since been adopted by many other research groups around the world. But unlike most of these others, CMRE has continued to eschew the use of “off-the-shelf” networks trained on optical imagery, instead opting to leverage a large in-house database of MUSCLE synthetic aperture sonar (SAS) imagery that has been collected over the last decade during sea experiments in various locations. At the same time, we have incorporated extensive domain expertise into the network design, which has enabled the successful development of tremendously smaller networks (trained “from scratch”) that still achieve excellent classification performance [2-3]. This philosophy of tailoring the algorithms to the specific sonar modality has also facilitated the use of alternative data representations with CNNs [4-6], including low-frequency acoustic-color data [7]. Relying on off-the-shelf networks, in contrast, would have closed these rich research avenues. Our work has also demonstrated the applicability of transfer learning, showing the feasibility of applying to other sonar sensors the CNNs that have been trained on MUSCLE data [8-9]. As such, there are promising opportunities for transitioning the CMRE-developed CNNs to similar, but distinct, systems of NATO nations in the near future.

2.2. Target clustering

The goal of Target Clustering algorithms is to merge multiple detections of the same target into a single entity, or cluster. Ideally, the formed cluster will benefit from the multiple detections of the same target, by having a better estimate of the target's position. In order to do so, clustering algorithms usually build on data provided by an ATR software or from a human operator. In particular, they can use information of the location of a given detection in a tile, together with an associated score. These detections are fused into multiple target clusters, taking into account the estimated navigational drift of the vehicle. However, in some situations the ATR can fail completely to detect the target. On the other hand, the ATR can sometimes detect a target but assign it a low score which then, depending on the acceptance threshold, can cause a target to remain disregarded. Figure 2 provides a schematic diagram of the interface between ATR and Target Clustering.

In an ongoing effort to address Target Clustering, CMRE is proposing a newly developed probabilistic target clustering algorithm. Motivations for a probabilistic algorithm are two-folded. First, it is desirable that the target clustering process provides not only the location of a given target, but also an indication of the uncertainty of such estimation, in a mathematically sound and robust approach. Secondly, the use of a probabilistic framework also favours a closer integration with other aspects related with target location accuracy, as for example navigation accuracy of autonomous vehicles, exploration and target reacquisition search behaviours, or even planning and evaluation for systems of systems MCM operations. For instance, the navigation accuracy of a vehicle will have a definite impact on the location of the targets it detects. At the same time, knowledge of the location of a target as well as its uncertainty can be very relevant, particularly in multi-vehicle MCM missions, where surveying and target reacquisition tasks might be performed by different vehicles.

The proposed algorithm, based on a Probability Hypothesis Density (PHD) filter, uses Random Finite Sets (RFS) to model both the collection of individual target states and the collection of observations. Perhaps the biggest advantage of the PHD filter, is the fact that it does not require an explicit data association step. When addressing problems such as target clustering or multiple target tracking, characterized by multiple simultaneous observations, the data association step can be quite cumbersome, and even computationally very demanding or even intractable. At the same time, the usage of RFS, as opposed to random vectors, is a more suitable formulation for addressing varying number of targets, target (dis)appearance and spawning, the presence of clutter and association uncertainty, false alarms and missed detections or even extended targets.

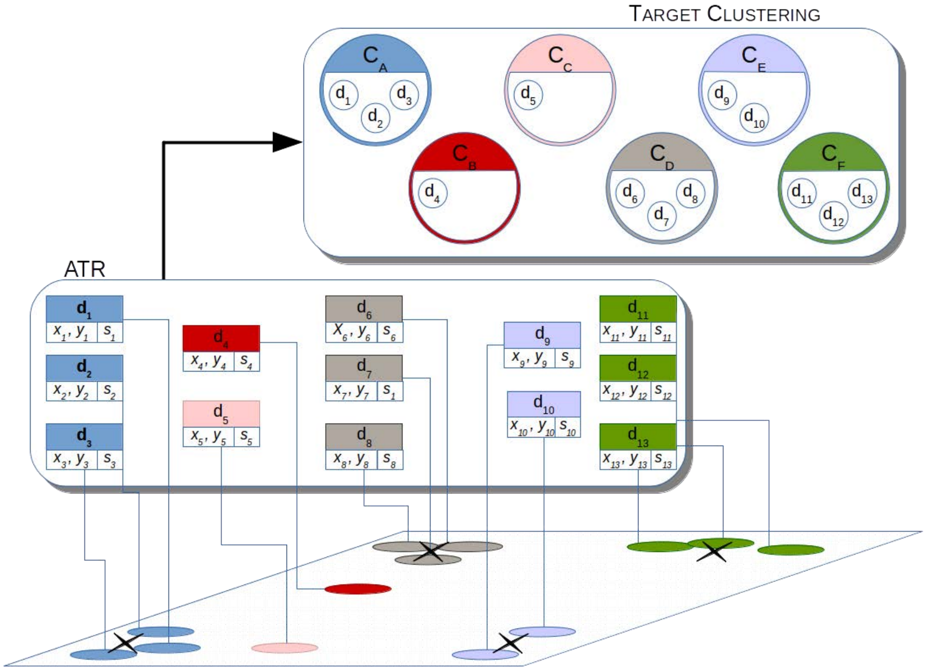

Fig. 2: ATR and Target Clustering algorithms. The ATR algorithm provides 11 detections of existing targets, and false alarms. The Target Clustering algorithm merges the 13 detections into 6 different clusters, corresponding to the 4 existing targets, and to the 2 false alarms.

3. IN SITU PERFORMANCE EVALUATION

At the CMRE we developed an in situ performance evaluation framework, which aims to predict the probability of the ATR *not* detecting a target. We combine these probabilities into a Residual risk map (RRM) of the survey area [10]. RRMs give us a way to quantify the performance of the AUV during a mine-hunting mission. Similar to currently available software such as MCM Expert and DARE, these RRMs can aid in estimating the percentage of targets that have been detected. Unlike the methodology currently in use, the RRM framework is designed to properly handle side-looking sonar imagery and, instead of providing a single number expressing risk or coverage, the RRM can be used to identify which parts of the survey area should be revisited for closer inspection, or if time and resources do not permit this, which areas should be avoided. The algorithm through which we can construct the RRM is based on the range, i.e. the distance between the sonar sensor and the target, but crucially also on *through-the-sensor* features such as ping-to-ping correlation, and metrics that are sensitive to the texture of the image that in turn are correlated with different types of sea bottoms [11]. The algorithm is flexible in the sense that it is agnostic to the specific sensor hardware and ATR type used, as long as we have reference data to constrain model parameters. This means that RRMs can be generated by multiple AUVs that are not necessarily identical in load-out. This is ideally suited for cases where we want to deploy multiple assets in parallel to accelerate the survey.

Through the use of Bayesian statistics, we not solely have a point estimate of our RRM (i.e. a single number per grid cell), but we also calculate a confidence interval. This means that the presence or absence of certain features, e.g. the presence of acoustic shadows, will not only tell us how strongly the probability of detection will increase or decrease, but it will also tell us the amount of uncertainty it will introduce in our estimate. This can be particularly useful when we wish to fuse RRMs from different vehicles with different sensors, since we can use these uncertainty estimates to weight their contributions to the combined RRM.

Fig 3 shows an example RRM. The homogeneous red areas indicate grid cells not covered during the survey. The vertical green strip in the left hand side of the RRM is the results of the MUSCLE covering this strip twice, leading to an increase in the probability of detection. Finally, red and orange "veins" running through the RRM are the result of sand ripples being present there, causing a decrease in the probability of detection. To bring down the estimated residual risk, these areas should be revisited and viewed from a different angle to avoid the acoustic shadows caused by the sand ripples.

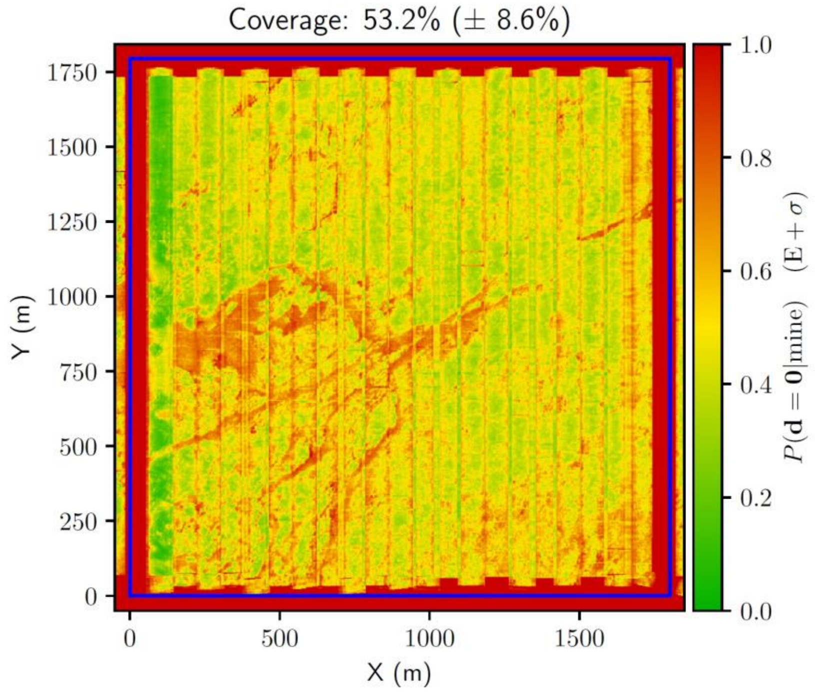

*Fig. 3: RRM constructed from data recorded by the MUSCLE during ESPMINEX18. The colour values express the probability of a hypothetical target going undetected. To integrate our uncertainty estimates into a single map, we penalize uncertain areas by adding the uncertainty (σ) to the expected value (*E*). The blue border indicates the borders of the survey area.*

4. AUTONOMY

Autonomy is the mechanism through which human operators can be displaced or altogether removed from a mine countermeasures mission. Autonomy situated aboard unmanned systems uses sensor information and the results of signal processing algorithms (e.g. those described in Section 2), and algorithms for adaptation and intelligent decision making to drive mission execution. In our programme, we delineate two layers of autonomy --- single and multi-agent. Single agent autonomy encompasses the autonomy solution(s) onboard a single asset for performing any of the tasks that said platform might perform, e.g. [12-14]. The multi-agent layer has a larger scope, and is responsible for the management of multiple autonomous single-agents to perform missions collaboratively [15]. In this section we discuss an example of a current single-agent autonomy solution, adaptive survey planning for improved data quality; and in general terms the approach we take to multi-system collaborative mission execution.

4.1. Adaptive Survey

CMRE has developed a coverage path planning approach for the MUSCLE that combines efficiency and through-the-sensor metrics to inform the track orientation of an AUV [12]. Following the results from the RRM in Figure 3 [rrm map], a considerable decrease in probability of detection is caused by sand ripples on the seabed. Employing an adaptive survey instead of a predefined path allows the vehicle to react immediately to unfavourable environmental conditions and could eliminate the need for revisiting the area.

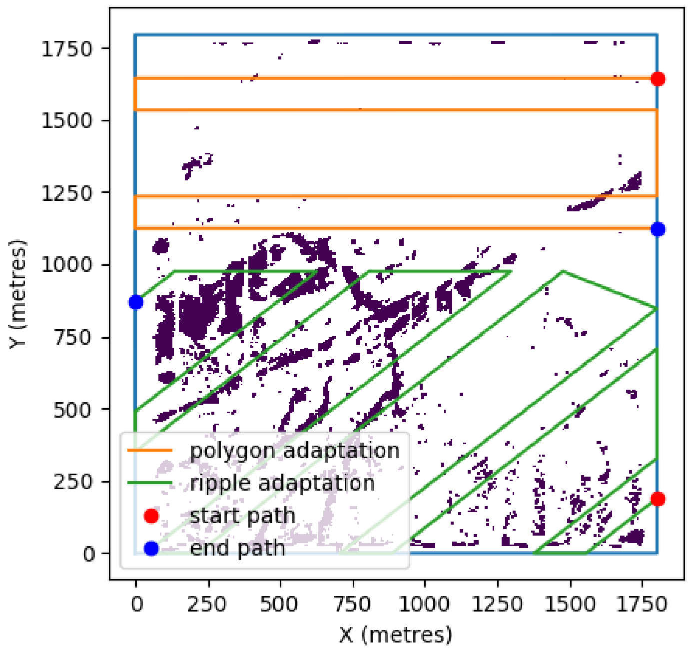

Fig. 4: Adaptive survey based on RRM data products from ESPMINEX18. The simulated mission starts with the orange tracks and takes as an input only the spatial parameters of the survey area – the tracks are adapted to the survey area shape. With each track line, a layer of the RRM map from Fig. 1 is processed and updated. The AUV adapts to the discovered sand ripples by changing its tracks orientation, shown in green, and collects the data at an angle that optimises the data quality [12].

Figure 4 gives an example of an AUV adaptive survey using data products derived from the *in situ* performance evaluation shown in Figure 3 [rrm map]. At the beginning of the mission, it is assumed that only the spatial and temporal parameters of the mission are known to the AUV, but no seabed information is available in advance. The orange path of the vehicle adapts to the search area shape, with the aim to improve resource efficiency. Once a sand ripple field has been detected, the AUV changes its track orientation and follows a path along the ripples' ridges. At the new angle the vehicle can collect sonar data with less shadows, and increase the probability of target detection. Developing and improving new adaptive survey approaches allows collecting more reliable and high-quality data. Such strategies will also aid the safe waterspace management and efficient collaboration in a shared operational area for a heterogeneous network of manned and unmanned assets.

4.2. Collaborative autonomy

The rationale behind using multiple agents to perform mine clearance is the overall goal of accelerating mission execution. Given that a mine clearance mission includes dynamic, highly heterogeneous tasks (from wide area survey to target revisit and identification), the creation of a federated squad allows the specialisation of systems for specific tasks, and allows for a greater rate of clearance. Our approach, architecturally, delineates a layered separation between the execution of tasks (known as capabilities) and the invocation or allocation of those tasks, at a network level, as depicted in Figure 5.

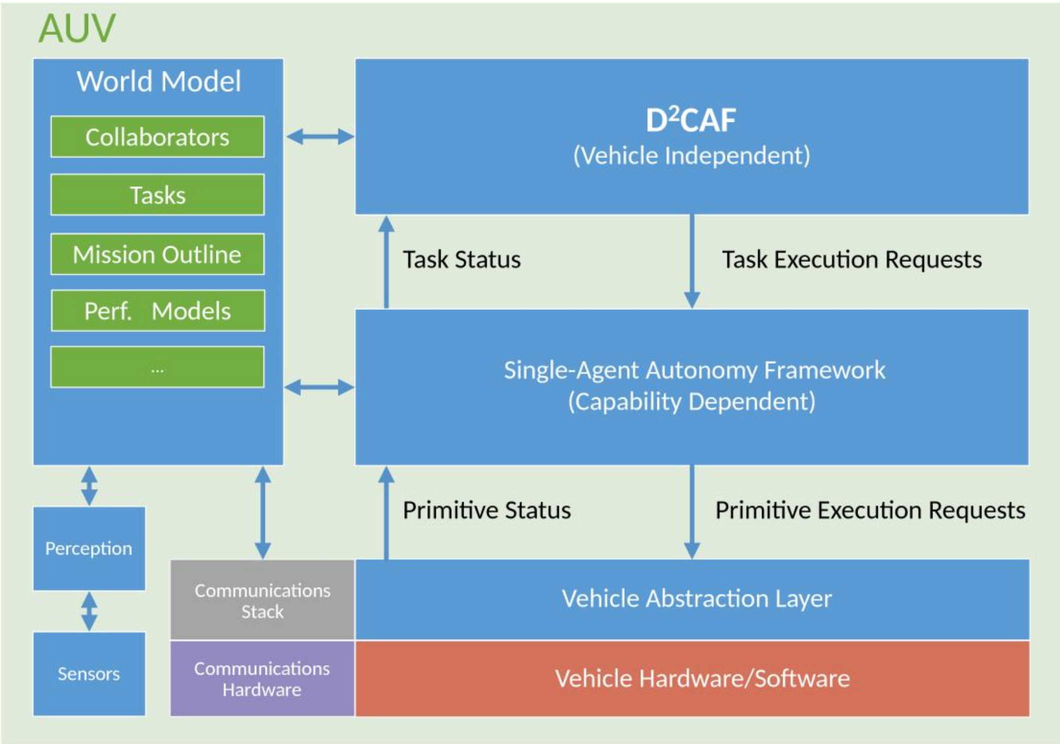

Fig 5: Layered architecture of CMRE's ANMCM assets. D2CAF, our solution for managing task allocation and dissemination within a heterogeneous squad, sits above single-agent frameworks, which might be different for each asset. The task execution interface (the lines between the upper two layers) shares the same interaction model between systems, independently of how the tasks themselves are performed.

The multi-agent layer is responsible for the management of the squad-level task objectives, their decomposition and dissemination within the fleet, and the allocation of the objectives to appropriate members of the squad. The single-agent layer simply provides a task interface, exposing its internal capability of task execution, to be invoked by higher-level decision-making. In this way, the intelligence or novelty of task execution is compartmentalized in a modular away, separate from the mechanisms which decide to invoke the execution of such a task. We have developed a framework, the Distributed/Decoupled Collaborative Autonomy Framework (D^2CAF), [15], which provides infrastructure and tools in which to house prototype algorithms handling the distributed task allocation problem. This framework has a task-centric model, where tasks represent work to be done in relation to a higher level mission goal, and the performance of such tasks can and must be scheduled and allocated to platforms that have appropriate capabilities. The framework itself is not domain specific, with domain specialisation being represented by the definition of a task dictionary --- the framework itself does not care about the specifics of the task types, but only about the abstract representation of the performance of those types. The framework is designed to allow *distributed* algorithms to be embedded, without a centralized master node. Moreover the framework can be used to amalgamate various systems into a federated squad by *decoupling* the task execution and allocation problems, and even allowing D^2CAF agents to run in systems other than those autonomous systems that they represent. This configuration allows legacy assets to be incorporated into a more performant squad using off-the-shelf interfaces for command and control.

5. HIGH RESOLUTION LOW FREQUENCY SYNTHETIC APERTURE SONAR

Over the last decade, Synthetic Aperture Sonar (SAS) has become a tool of choice for Mine Counter Measure (MCM) operations. The high resolution acoustic imaging output coupled with a constant resolution in range has drastically improved Automatic Target Recognition (ATR) algorithm results in term of detection rate and probability of false alarm. A major effort in research and development has been made for the high frequency SAS systems which provide surfacic information of the seabed and prone objects. Improvised Explosive Device (IED) and buried targets however still may remain extremely challenging to detect and classify especially in difficult and cluttered environments. A Low Frequency (LF) system aims to counteract this particular problem: lower frequencies provide greater sound penetration into the seabed and the potential target, permitting additional detection and recognition information; LF also propagates further in water, potentially allowing longer imaging range.

The CMRE has been developing his own high resolution low frequency synthetic aperture sonar (HR-LFSAS) prototype to tackle the problem of underwater mine classification and identification. The design of this system is based on a 2D transmitter array and a 2D receiver array, where elements can be driven individually. The development of such a system is not without challenges [16], but it also solves intrinsic problems linked to low frequencies such as size, bandwidth or energy output [17]. The 2D array receiver is also fundamental as it allows 3D data collection, which is one of the main interesting features that low frequency systems offer.

Over the last year, the HR-LFSAS team has developed theoretical tools to better understand and exploit the LF information gathered by such a system. These include:

- a study of the SAS PSF (Point Spread Function) [18], which is in essence the building block of SAS imagery and is fundamental for multi-chromatic analysis;
- the design and the impact of the waveforms [19] in order to maximise the efficiency of the system; and,
- the potential advantages of super-resolution imaging algorithms [20] for operators or for improving the performance of automatic recognition algorithms improved.

An important aspect of the development and the improvement of the system resides in realistic representations of the interactions between LF acoustic waves and an object of interest. Part of our effort is focusing on developing realistic, physics-based acoustic wave simulators [21–23] to apprehend the complex backscattering phenomena, enable the elaboration of a large simulated database and develop efficient strategies for information extraction. In particular, new ATR algorithms benefit greatly from synthetic representative datasets. As an example, we showed in simulation the potential of the LF system to differentiate materials of an object [24].

Although the LFSAS prototype is still in construction, several trials have taken place in 2018 including the first phase of the calibration of the transmitter array [25] at Loch Goil in Scotland, and the rail-based TORHEX'18 (Target Oriented Rail-based Experiment) [17, 26] at La Spezia, Italy. TORHEX'18 was focused on acquiring relevant scientific data with the upgraded hardware, and the full transmitter array. The rail facility was utilised to acquire data for LF aperture synthesis, and the first LFSAS images of relevant objects have been analysed and processed showing the great potential of this system for MCM operations.

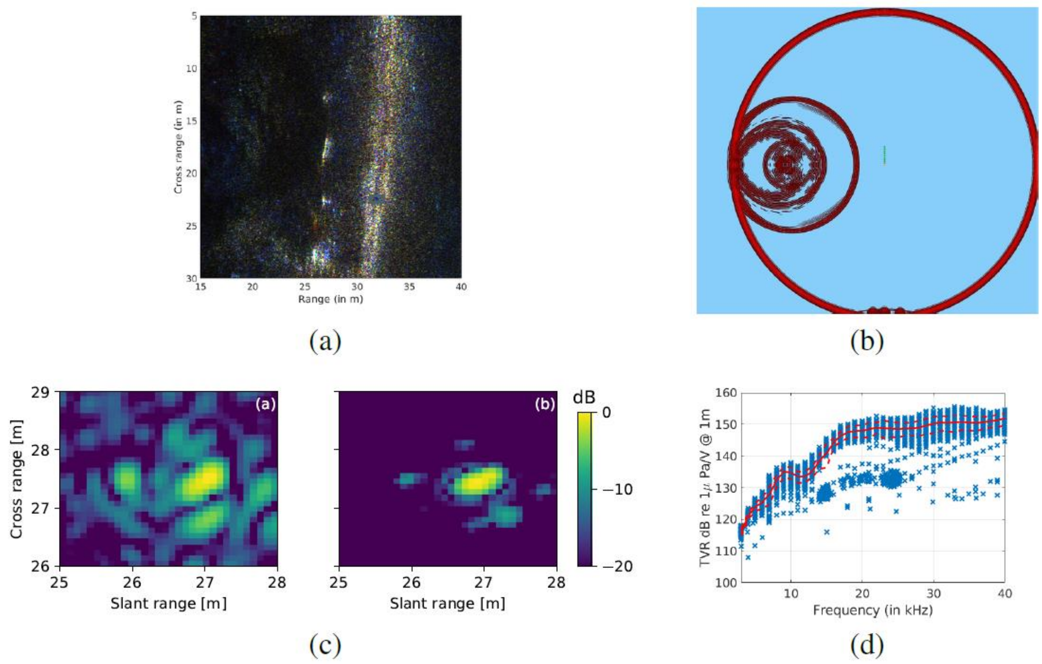

Fig 6: (a) Multi-chromatic LFSAS image from TORHEX'18. (b) PVC shell response computed with SPECFEM2D. (c) Sparse LFSAS image reconstruction with the DMM algorithm. (d) Statistical Transmit Voltage Response

6. CONCLUSIONS AND FUTURE PROSPECTS

The CMRE mine countermeasures program of work is based on a multi-disciplinary approach, which develops complementary techniques to bring together heterogeneous autonomous systems and ensure the best possible outcome of a system-of-systems mission. The strength of the centre is its ability to rapidly prototype new algorithms and concepts at sea in realistic conditions. The ANMCM group will continue to develop further autonomy, automatic identification, navigation remediation, and low frequency solutions for difficult cluttered environments and buried targets.

The work will seek to expand its operational envelope to very shallow waters, over-the-horizon overt and covert and address the potential new mine threats that may challenge the current technologies. This will entail the development of new high resolution technologies to address the very shallow water conditions, adaptable vehicles to difficult surf zone environments and the increase in automated machine intelligence and decision making capabilities.

The CMRE regularly releases papers and reports to highlight the advances of the research and will periodically release software relating to the work undertaken. In particular, a first version of D2CAF is now downloadable for national defence laboratories if eligible. The centre continues to work in bi-lateral efforts with nations actively to transfer knowledge and algorithms for particular national systems. The Centre is also an active participant in NATO working groups focused on Naval Mine Warfare applications and regularly promotes novel and modern products such as the risk maps to operators and command and control.

7. ACKNOWLEDGEMENTS

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