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A Robotic Cooperative Network for Localising a Submarine in Distress: Results From REPMUS21

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Abstract— **Autonomy, cooperation and data fusion can increase the performance of robotic networks in many underwater applications. In this paper, we describe a novel occupancy grid (OG) based perception layer, and its use for controlling a network of autonomous underwater vehicles (AUVs), sensorised with passive sonars. Data fusion between the robots' bearing-only measurements (typical of passive sonars) enables the estimate of target position. The developed OG framework exploits networking and the spatial diversity provided by the multi-robot system. The perception layer was integrated in the intelligent Cooperative Autonomous Decision Making Engine (iCADME) control architecture and validated for the first time in the Robotics Experimentation and Prototyping MUS (REPMUS) Exercise, held in Portugal in September 2021.**

Our robotic network participated in a technical demonstration, whose main objective was to localise a bottomed submarine which emitted a periodic help request acoustically during a simulated distress situation. We report results which are one of the first examples to demonstrate how cooperative robotics, supported by data fusion, can be effective in a passive sonar scenario. They also confirm the viability of adopting such solutions in real-world applications, characterised by poor communications and challenging environments. What was achieved at REPMUS21 clearly demonstrates how a network of cooperative robots can improve search & rescue operations of a submarine.

I. INTRODUCTION

Underwater robots can significantly improve the performance of traditional ship-based operations [1]–[4]. They can exploit their sensing and movement capabilities and have the potential to increase the mission's spatial and temporal resolution, leaving the ship available for other tasks [5], with an overall reduction of mission costs.

Building upon single-platform capabilities, robots can cooperatively create an intelligent network. A robotic network enables the exploitation of the spatial diversity offered by the different nodes, and can leverage data-fusion techniques to enhance the sensing performance of single autonomous platforms, typically of inferior quality when compared to ship-deployed instruments [3].

However, to develop and control such multi-robot systems, we have to solve several challenges posed by the underwater domain [3], such as the severe limitations of the acoustic communication link in terms of bandwidth, range and reliability [6].

At the NATO STO Centre for Maritime Research and Experimentation (CMRE), we have been facing such challenges in the development of our robotic networks for surveillance applications [3], [7]–[10]. Such networks, composed of fixed (buoys or bottom-nodes) and heterogeneous, mobile nodes, are mainly sensorised with sonars [3]. The approach to control these complex multi-robot systems in the challenging communication-limited underwater environment pivots on autonomy, data fusion and inter-node cooperation [8]. Cooperative autonomous decisions of the robotic nodes can indeed enable the network to operate effectively without a continuous and reliable communication link with a command and control (C2) centre [8], [10].

Recently, CMRE has been developing several passive sonar sensing solutions on board robotic platforms of different natures [3], [9]–[11]. Passive sonars listen for the distinctive noise radiated by targets as they operate in the ocean. Even if the detection range is generally lower than active sonars', a passive sonar system can remain covert and facilitates target classification. However, differently from active sonar, which can compute both range and bearing measurements, the passive signal processing chain produces bearing-only contacts [9], [11], [12]. Convincing solutions need to be found for distributed sensing, data processing, autonomy and communications, considered the limitations imposed by the acoustic channel which hampers the inter-node data exchange.

This paper focuses on facing such challenges for controlling the CMRE passive network during a technical demo (TD) of a search & rescue mission for a submarine in distress (DISSUB) [13], held off the coast of Portugal during REPMUS21 trial, in September 2021. We describe the perception layer developed to support the inter-node data fusion and to exploit the spatial diversity of different network robots. It relies on occupancy grid (OG) [14]–[18] mapping techniques, in particular on an adaptation [19], [20] to the standard OG method. OG maps show the probability of each grid cell containing a target. The method iteratively builds an OG map from successive acoustic measurements and provides a way to fuse bearing-only measurements from different assets in real-time to estimate the submarine position. The proposed map-building approach supports cooperative decision-making [8], [10], complementing and offering a valuable guidance to reactive and behaviour-based strategies [3]. We also detail the solutions adopted to execute the perception layer on board the CMRE network.

During REPMUS21, for the first time, the iCADME [8] control architecture, in its task-oriented version, managed our robotic network. Two Ocean Explorer (OEX-C) au-

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tonomous underwater vehicles (AUVs), towing linear arrays of hydrophones, were tasked to survey an area to search for a submarine, positioned on the seafloor and emitting an acoustic signal. The AUVs generated and exchanged bearing-only measurements. The produced information was fused in real-time to estimate the submarine position. For the first time, the CMRE network was integrated with the REPMUS central C2 centre by using the Collaborative Autonomy Tasking Layer (CATL) standard message model for federated autonomous collaboration and interoperability [21]. The estimated DISSUB position was successfully relayed to a collaborator robotic team from the University of Porto, which finally confirmed its position with side scan sonar surveys [13].

We report and discuss results which are one of the first examples in the literature to show the clear benefits of advanced cooperative autonomy and data fusion for controlling a complex robotic network in a passive sonar scenario. They also demonstrate the viability of adopting such strategies in a real-world challenging scenario, characterised by poor communications and a noisy environment.

II. A Perception Layer Based on Occupancy Grid Mapping

The perception layer developed for controlling the robot mission is based on occupancy grid (OG) mapping [14], [17]. The method requires discretisation of the environment into a collection of small cells, each of which is considered as being either completely occupied or completely empty. OG mapping strategies fuse successive noisy and uncertain measurements into estimates of the likelihood of each cell being either occupied or empty. Let C be the number of cells in an OG map. $m_{1:C}$ denotes the collection of all binary cell states, and $z_{1:t}$ is the collection of all measurements. Then, considered as a Bayesian C-dimensional binary estimation problem, all information about the state of the map would be contained in the posterior:

$$p\left(m_{1:C}|z_{1:t}\right) \tag{1}$$

The number of possible maps is 2^C, and so it is usually prohibitive to store or compute this full posterior. Therefore, OG mapping methods typically seek the marginal posteriors for the occupancy of each cell

$$p\left(m_i|z_{1:t}\right) \tag{2}$$

Popular standard Bayesian update algorithms assume that the current measurement is independent of all other measurements predicated on knowledge of the cell currently being updated. This assumption largely simplifies the computation of the marginal posteriors, enabling to handle the mapping problem as a set of C independent binary estimation problems [14]. However, a sensor measurement typically involves multiple cells. Therefore the assumption is generally incorrect and consequently the marginal posteriors computed by the standard algorithm are inexact.

OG maps have been classically used to map the environment of a robot [14], [22]. In our application, we apply them

Algorithm 1: IP ALGORITHM $(\{l_{t-1,i}\}, \{P_i^t\}, z_t)$

Time starts at instant $t = 1$
for *all cells* m_i **do**
  if m_i *is in the perceptual field of* z_t **then**
    if $z_t = 1$ **then**
      $\widetilde{P}_i^t = \frac{e^{l_{t-1,i}}}{1+e^{l_{t-1,i}}}$
      $l_{t,i} = \log \frac{1-\left(1-P_f^t\right)\left(1-P_i^t\right)\prod_{s\neq i}\left(1-P_s^t\widetilde{P}_s^t\right)}{1-\left(1-P_f^t\right)\prod_{s\neq i}\left(1-P_s^t\widetilde{P}_s^t\right)}$
    end
    else
      `// ` $z_t = 0$, z_t `results in a non-detection`
      $l_{t,i} = \log\left(1 - P_i^t\right) + l_{t-1,i}$
    end
  end
  else
    $l_{t,i} = l_{t-1,i}$
  end
end
return $\{l_{t,i}\}$
where $l_{0,i} = \log \frac{p(m_i)}{1-p(m_i)}$ and is called log odds form of the probability. It is trivial from $l_{t,i}$ to recover $p\left(m_i|z_{1:t}\right)$, since $p\left(m_i|z_{1:t}\right) = \frac{e^{l_{t,i}}}{1+e^{l_{t,i}}}$

to quantify the probability of the presence of targets in a region of interest. The binary state of grid cells is redefined to denote the probability of target presence or absence. It is important to underline that the approach used does not make assumptions on the presence of a single target in the area, and does not suffer from the difficulties raised by data association, usually present in tracking approaches [15]. To apply an OG method to the addressed scenario we have to: (i) define a suitable sensor model, (ii) select a map update and (iii) handle a dynamic world.

A. A forward sensor model

In our scenario measurements consist fundamentally of target presence (detection) and absence (non-detection). If we accept the binary nature of detections ($z_t = 1$) and non-detections ($z_t = 0$), a simple model for the probability of having a detection given complete knowledge of the locations of all targets in the map (i.e. the true state of each grid cell) is [17], [19]:

$$p\left(z_t = 1|m_{1:C}\right) = 1 - \left(1 - P_f^t\right)\prod_{i\in O}\left(1 - P_i^t\right) \tag{3}$$

where P_i^t is the probability that sufficient signal from cell i arrives at time t to trigger a detection, P_f^t denotes the probability that a false alarm occurs at time t, and the product is over all occupied cells (O) in the map. The probability of non-detection is simply one minus this quantity.

The sensor model described in (3) is a *forward sensor model*. This means that it denotes the probability of a measurement given the map. The standard Bayesian occupancy grid mapping algorithm requires the inverse marginals of (3), i.e. $p(m_i|z_t)$. It is shown [19] that (3) is analytically both invertible and marginalisable.

We assume a sensor capable of producing bearing-only measurements $\{\theta_i\}$. P_i can be written as:

$$P_i = Pp_i \cdot Pd_i \tag{4}$$

where Pp_i is the probability that the target, given a measurement θ_i, is present in a certain cell i, and Pd_i is the probability of detection for a target located at cell i. For computing P_i given a measurement θ_i, we first compute the related standard deviation σ_{θ_i}, function of bearing and array features [17]. Bearing uncertainty is assumed as a random variable Θ, with $\Theta \sim \mathcal{N}(\theta_i, \sigma^2_{\theta_i})$. The range uncertainty is modelled as a random variable R following a uniform distribution from the minimum to the maximum range. This enables to compute the Pp_i for all the cells belonging to C_D, that is the set of all the cells that may have originated the detection. Finally, by using a model of the Pd as a function of bearing and distance from the sensor we can finally compute the P_i quantities, needed by the map update algorithm [17].

B. An alternative map update

An important feature of our application is the small number of cells expected to be occupied by targets (or detectable objects, such as passing vessels). This implies that the prior probability of occupancy associated with each cell is much lower than is typical in OG maps, such as the layout of a building constructed from laser range-finder data [14]. In such scenarios, an alternative map update rule proposed in [19] often produces better results than the standard algorithm [14]. This method is named Independence of Posteriors (IP) since it involves conditional independence assumptions and its pseudo-code is shown in Algorithm 1. The method, for environments with low priors like the one addressed in this paper, produces maps [19], [20] which are more consistent with the true number of occupied cells and are less sensitive to the choice of the algorithm parameters (e.g. the prior used to initialise the map cells). We note that its computational and storage costs are equivalent to the standard algorithm.

Moving targets imply a dynamic world. This means that the mapped environment changes over time, and the cell occupancy cannot be assumed to be static. To tackle this, we have developed an ageing technique relying on a Markov chain [23], which was demonstrated recently at sea [10] as being capable of improving the tracking of a moving target. However, in the DISSUB experiment, the submarine was stationary and the ageing technique was not used. Further details about the method can be found in [17], [19].

C. Fusing single robot maps to estimate target location

Each robot integrates the real-time measurements produced on board to create its map, called the "local" map. It also produces a "remote" map, by using the collaborator measurements received via acoustic communications. Then, a "fused" map, $p_f(\mathbf{m})$, is computed by multiplying the occupancy of each cells of the two maps. As the metrics to quantify the quality of target localisation, we use the Laplacian of the fused map $p_f(\mathbf{m})$, that is $LP_f(\mathbf{m}) = \nabla^2(p_f(\mathbf{m}))$. The Laplace operator is a differential operator consisting in the divergence of the gradient of a function on a Euclidean space. If we consider $p_f(\mathbf{m})$ as a scalar field, cells with negative values of $LP_f(m_i)$ are characterised both by high occupancy probability and are surrounded by cells with lower occupancy probability. Cells with negative values are therefore likely to contain a target. These are exactly the conditions we seek for accurately estimating the target position.

III. REPMUS21 Technical Demo: localising a submarine in distress

The DISSUB TD took place in the context of the REPMUS21 exercise, held in the Atlantic Ocean off the coast of Portugal in September 2021 [13]. The objective of the DISSUB TD was to demonstrate the effectiveness and feasibility to use a robotic network in a search & rescue mission for a submarine, and to develop new procedures for operations supported by digital underwater communications. JANUS [24], the first open and internationally adopted digital underwater communication standard (promulgated as a NATO standard-STANAG 4748 [25] in 2017), was used for enhancing the information exchange and the situational awareness of the DISSUB.

The operational scenario is reported in Fig. 1. A submarine played the role of the cooperative DISSUB. She positioned on the seafloor and started to transmit periodically a signal, simulating a distress situation. The CMRE robotic network was composed of a Wave Glider [26], [27] surface vehicle and two moored surface buoys for creating the communication infrastructure. These assets had an acoustic modem and a radio device, and acted as communication gateways for the AUVs. They were also equipped with JANUS capable modems to enable the operators on the NRV Alliance, the C2 centre of the experiment, to communicate with the DISSUB. The NRV Alliance transmitted information received from the robots (e.g. submarine estimated positions, asset locations) to the Maritime Operation Centre (MOC), by using the SCI-288 messaging protocol for autonomy [21]. The mobile sensing nodes were the two CMRE OEX-C AUVs (named Harpo and Groucho). They are 5.5 m long, 0.53 m-diameter robots with a typical endurance of 72 hours of operations at a cruise speed of 1 m/s. The AUVs towed linear arrays, deployed approximately 3.5 m behind the vehicle [7], [28].

Each network node was equipped with 7/17 kHz Evologics S2C low-frequency modems [29] for underwater acoustic communication and with Wi-Fi modems for RF communications. The CMRE Cognitive Communications Architecture (CCA) [30] was deployed on each node, and employed to support the communication and networking capability, including JANUS. Finally, a robotic team from the University of Porto - Faculty of Engineering (FEUP), composed of two Lightweight AUVs (LAUVs) [31], had the task to confirm the DISSUB position, conducting a survey around the location

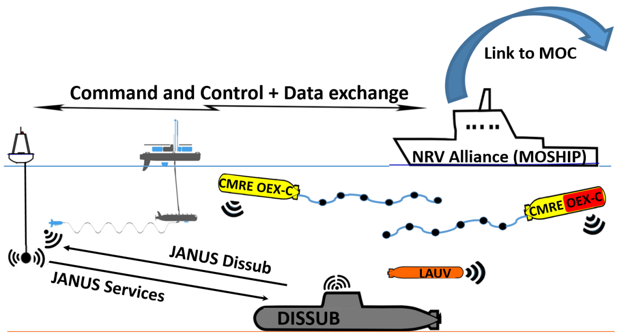

Fig. 1. DISSUB TD scenario: robotic network, composed of heterogeneous and cooperative vehicles, in support to DISSUB search & rescue. Adapted from [13].

computed by CMRE network. Further details can be found in [13].

The described OG framework was integrated in the iCADME autonomy architecture [8] (see Fig. 2).

In REPMUS21, for the first time, the task-oriented version of iCADME was used at sea. iCADME is a three-layer, hybrid [33] control architecture to handle cooperative mission planning and and execution. It runs in a Mission Oriented Operating Suite (MOOS) middleware [34] environment. MOOS-IvP is a set of open source C++ modules, built on the publish/subscribe paradigm, for providing autonomy on robotic platforms. iCADME is executed on the so-called "backseat" computer. According to the "backseat-driver" paradigm [28], [34], the backseat computer runs the "intelligent" robot software, such as signal processing and autonomy, and produces commands for the "frontseat" computer that generates references for the actuators and provides the interfaces with the on board sensors.

Depending on the task in execution, the *Control Layer* activates a different set of behaviours. Each behaviour produces desired commands for the robot. Outputs are reconciled by the `pHelmIvP` MOOS application, which uses IvP interval programming technique [35]. The final commands (typically speed, heading and depth) are transmitted to the frontseat computer.

The novel iCADME task-oriented architecture enables multi-task missions, facilitating the user in the creation of new task/behaviors and in the mission design and configuration. The driving principle is the emphasis on modularity, for supporting the creation of complex missions, by assembling a portfolio of tasks, connected with logical/temporal conditions. Perception and decision-making are decoupled from action. This is done by developing a hierarchy of tasks, in charge of perception and decision-making, in our case *Area survey OG*, and a hierarchy of behaviour strategies, which are the interface with the Helm behaviour sets (the behaviour strategy commands to the *Control Layer* which Helm behaviour set to activate). The association between tasks and behaviour strategies is dynamic and done at run-time, achieving a trade-off between class inheritance and class composition. For instance, our *Area survey OG* task can be associated either with a *Racetrack* or a *Loiter* behaviour strategy, with different robot movements, though using the same perception and decision-making algorithms. The iCADME

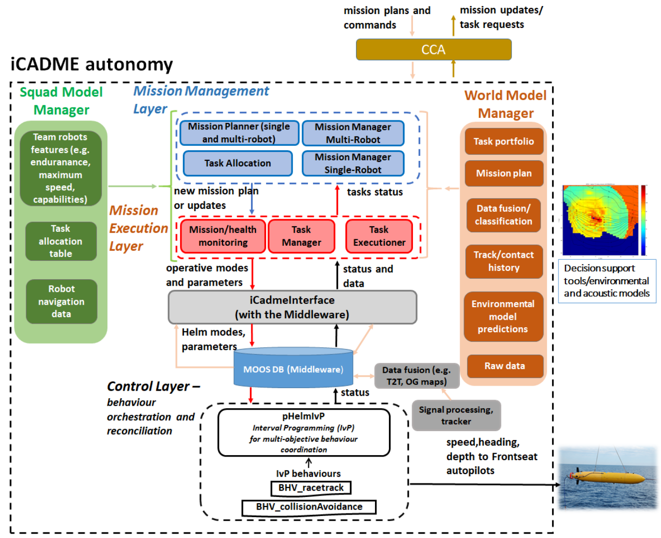

Fig. 2. The three layer iCADME autonomy architecture with the information flow.

separation between the logic for task invocation, allocation, and execution facilitates its use on heterogeneous robots and the system and mission testing. In our experience, these are crucial factors during experiments at sea.

In the DISSUB TD (see Fig. 3), each OEX-C AUV executed a passive signal processing chain developed for uniform linear arrays (ULAs) [9] to produce bearing contacts. The signal processing chain used linear beamforming, local Signal-to-Noise-Ratio estimation, and contact clustering to generate a set of bearing measurements that is passed to the OG framework to produce local occupancy maps. Noise measured by the array was recorded in a file and then processed to produce bearing contacts, which, together with the platform position, are exchanged with the collaborator. The contacts received from a collaborator were incorporated to create the remote map. Then, the fused map was computed and used for estimating the target location. In addition, the messages were also processed by the C2 centre on the NRV Alliance, in which an iCADME instance was running to produce OG maps. This additional network fusion node was important to handle the mission and to monitor the robot operations. A scheme of the TD robotic network can be seen in Fig. 3.

Two solutions were designed to enable the robust execution of the OG framework in real-time on board the robots:

- A method to keep coherent and aligned in time local and remote maps, even in cases of missed receptions of collaborator messages.
- A redundancy communication scheme to handle missed collaborator messages. In each message, contacts from different past files are included, hence providing the robot with multiple opportunities to receive a set of contacts from a specific file.

IV. Results

The DISSUB TD was held on 18 September. The submarine positioned on the seafloor, at a depth of about 60 m. The CMRE network robots (the two OEX-C AUVs and

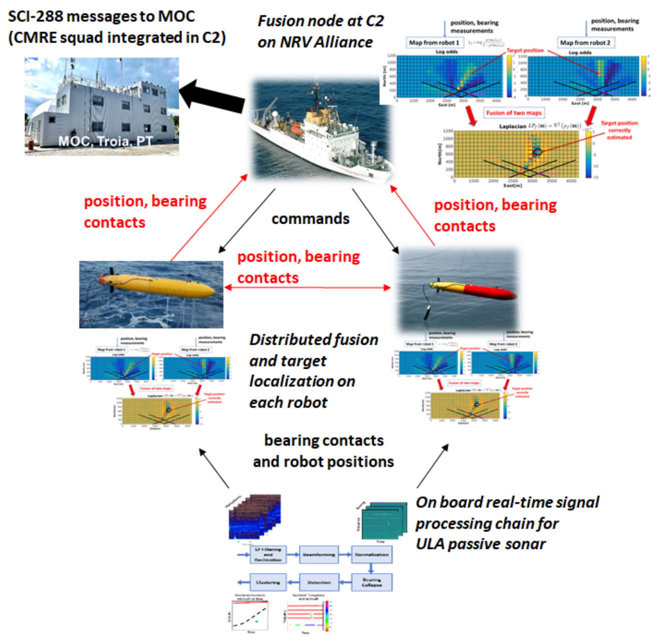

Fig. 3. Network scheme showing the data exchange between the OEX-C AUVs, the C2 centre on the NRV Alliance and MOC.

the Wave Glider) were deployed in the search area. The AUVs, by using digital underwater communications, started to communicate using an ALOHA protocol for medium access and interconnect with two CMRE moored buoys previously deployed in the area, which acted as communication relays with the C2 centre on NRV Alliance. The robots were equipped with ULAs and produced and transmitted bearing contacts every 20 s. During the experiment, a message had a maximum payload of 60 bytes. Using DCCL [36] encoding, each message could contain 21 contacts, other than the robot position. The redundancy scheme was set to transmit results from the three most recent produced files (7 contacts per file were selected for transmission). iCADME was in charge of managing robot autonomy and operations. To model the ULA features [3], the Pd used was function of bearing (maximum at array broadside[1] and set to 0 around endfire) and inversely proportional to range.

The two AUVs started their missions by executing a *Standby* task, loitering at 45 m and 35 m of depth. At 12:00 UTC the submarine started the transmission of sequences of short (300 ms) CW bursts at 3.3 kHz at the highest power (Source Level $\sim$ 182 dB re. 1 μPa @1m) on average every 30 s. Then, on each robot, iCADME started the cooperative *Area survey OG* task. Robots moved at 1 m/s along two rectangular paths (called racetracks), creating and sharing bearing measurements and using the OG-based perception layer to estimate the DISSUB location, computed as the cell of the fused map with the highest occupancy value. The two paths were 1800 m long and perpendicular, west-east for Harpo, and north-south for Groucho (see Fig. 4).

[1]Broadside refers to the target bearing relative to the array. If an array is towed straight behind the vehicle, broadside is 90° relative to the array heading. When a target is at broadside, the array gives the highest bearing resolution (lower measurement errors) and high Pd. On the other hand, a target at or near endfire, that is directly behind (bearing 180°) or in front of the array (bearing 0°), has a poorly resolved bearing and low Pd.

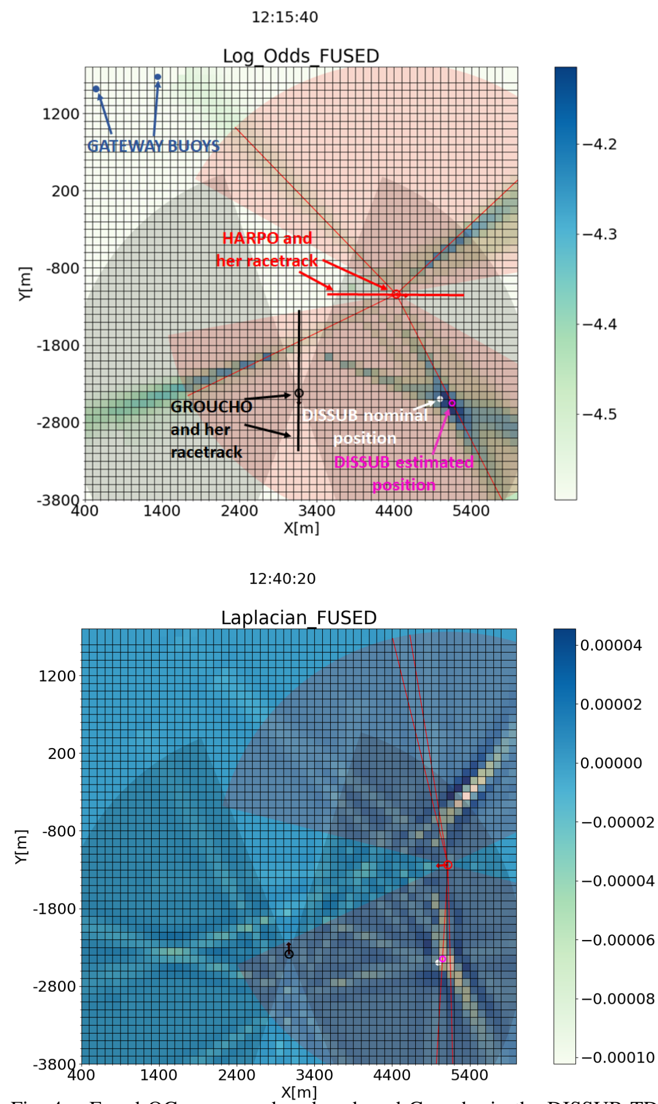

Fig. 4. Fused OG maps produced on board Groucho in the DISSUB TD. Cell dimension is 100 x 100 m. (Top) Log odds (probability) fused map at 12:15 UTC. The positions, sensor footprints and contacts (segments from robot positions), are indicated for Groucho and Harpo, respectively in black and red. Groucho, thanks to successful data fusion, is able to solve the port-starboard ambiguity and estimate the DISSUB position. (Bottom) Laplacian map at 12:40 UTC. The map was consolidated and enabled to reduce the estimate error.

The azimuth contacts for the robots are reported in Fig. 5, together with the groundtruth at the nominal DISSUB position. The port-starboard ambiguity, typical of ULAs [28], [37], is evident from the figure. It is in fact not possible in a linear array to discriminate if sound arrives from port and starboard direction, so for each measurement we produce both a left and right contact. The data fusion strategy presented here solves this issue.

Environmental and communication conditions were challenging during the mission. From 12:02 UTC to 12:42 UTC, the robots exchanged contact messages with an average transmission success rate of 22%. Furthermore, at the beginning of the mission, the robots experienced a period in which it was not possible to receive any collaborator contact messages at all. To the west of Groucho, the PRTN Hidra support vessel was operating, emitting noise, hence

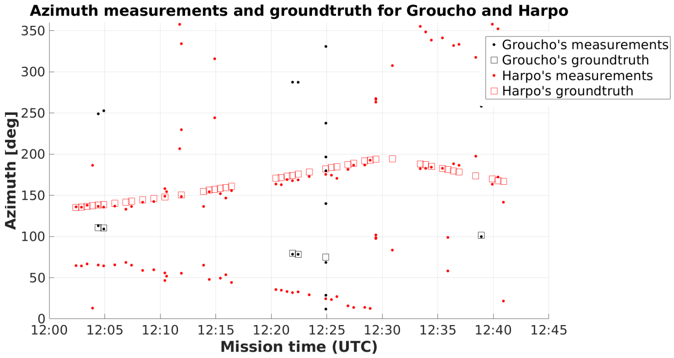

Fig. 5. Azimuth contacts and azimuth groundtruth for the DISSUB nominal position for the two robots. The low number of Groucho's contacts on target is evident.

hampering Groucho's signal processing. This resulted in a low number of Groucho's contacts, as can be appreciated in Fig. 5.

In Fig. 4, we show fused maps at two different times as produced in real-time by Groucho. Despite the low number of contacts produced on board, Groucho received some of Harpo's contacts, as visible in the figure. Thanks to successful data fusion, the robot estimated the DISSUB position accurately after 10 minutes from the mission start, with an error of 77 meters. This can be seen in Fig. 6, which reports the DISSUB localisation error for each robot. On the other hand, Harpo was not able to receive sufficient measurements from Groucho in the first part of the mission. Nevertheless, she was able to estimate the submarine position by exploiting her lateral movement with respect to the DISSUB, and finally receiving a contact from Groucho, thanks to the exploitation of the described redundancy scheme. This enabled Harpo to estimate the DISSUB position at 12:20 UTC, with an error of about 140 m.

During the whole mission, the positions of the robots and the estimated DISSUB positions were transmitted via SCI-288 messages to the MOC in Troia. Once the estimated positions by the two robots were in a good agreement, MOC passed the position detected by the CMRE network to the FEUP team for the deployment of the LAUV AUVs, equipped with a side scan sonar and underwater camera. One LAUV performed runs at 13:30 UTC on the received position and finally confirmed with side scan sonar images the location of the bottomed submarine. In parallel with LAUV operations, the CMRE Wave Glider (surface vehicle equipped with JANUS) converged in the area to establish a direct link with the DISSUB for data exchange and automated services via JANUS [13].

Executed by iCADME autonomy, the OG framework was effective to control the passive sonar network and to estimate the DISSUB position in real-world conditions. In a bearing-only scenario, the management of real-time data fusion and network spatial diversity become crucial. The OG-based data fusion strategy achieved this, computing the DISSUB position by solving the port-starboard ambiguity (see the intersection of the beams with increased occupancy probability in Fig. 4). The perception layer demonstrated robustness to limited communications and a noisy environment,

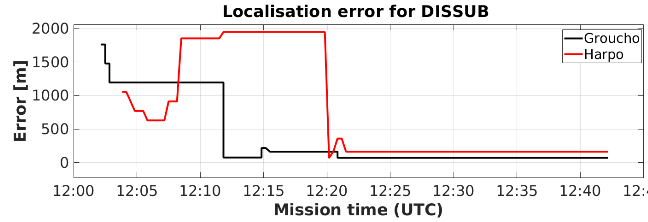

Fig. 6. Estimated DISSUB positions computed onboard the two robots during the TD.

also thanks to the redundant communication scheme. This confirms the importance of taking into account the aspects of robustness to environmental conditions beginning from the design phase.

V. Conclusion

Results from REPMUS21 TD demonstrate how cooperative autonomy and data fusion can increase the performance of a robotic network in an underwater surveillance application based on passive sonars. The short acoustic pulses emitted by the DISSUB were processed by the robots to produce bearing-only measurements. Data sharing was used to feed an OG-based perception layer, which fused the robots' measurements and exploited the network's spatial diversity to produce an accurate estimate of the submarine position. The iCADME autonomy, in its task-oriented version, was used for the first time to control the CMRE network at sea, facilitating the tuning of algorithm parameters, mission design and execution. The produced OG maps provide a common tactical picture, which is necessary for cooperative decision-making [10].

The reported results are one of the first examples to demonstrate how cooperative autonomy, supported by data sharing, can be effective in controlling a robotic network in a passive sonar scenario. They clearly show that these solutions can be actually adopted in realistic scenarios, characterised by poor communications and challenging environments.

Other than these scientific results, in REPMUS21 we achieved also important engineering and operational results. Experiments confirm that our robotic network is ready to be integrated with other robotic squads, by employing the standard and interoperable CATL messaging protocol for autonomy.

What was achieved at REPMUS21 clearly shows how digital underwater communications (JANUS) and a network of cooperative robots can be effectively used to improve the response time and increase the situational awareness of the DISSUB and rescue teams, thus resulting in more effective search & rescue operations.

Acknowledgments

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