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Gabriele Ferri, Andrea Munafò, Ryan Goldhahn, Kevin LePage

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# Towards Fully Autonomous Underwater Vehicles in ASW Scenarios: an Adaptive, Data Driven AUV Mission Management Layer

Gabriele Ferri, Andrea Munafò, Ryan Goldhahn, Kevin LePage

**Abstract**—We present an adaptive, data driven Mission Management Layer (MML) to manage the phases (surveillance, track prosecution and target reacquisition) of the mission of AUVs operating as receiver nodes in a multistatic network for littoral surveillance. Among the tracks produced by the on board tracker, the MML selects those which are likely originated by a target. The MML then issues commands to the vehicle Control Layer to trigger data-driven optimization behaviours to prosecute these candidate tracks.

Selecting few candidate tracks is indeed crucial since the addressed scenario usually presents many tracks hence resulting challenging from the tracking point of view. To select the candidate tracks, a metric is introduced to quantify their quality. It is based on the kinematic features of the target, on an acoustic model and on the quality of measurement-to-track associations. By selecting a limited subset of produced tracks, the MML can improve the benefits of using data-driven behaviours activating them only on interesting cues and reducing the time wasted to optimize tracks not related to a target. This aims at achieving a balance between the surveillance of the area of interest and exploitation of target cues (tracks). These features are essential for improving the overall mission performance and for an effective AUV decision making in realistic conditions. We present results from sea trials demonstrating the effectiveness of our approach and how the proposed MML can represent a step forward towards the full autonomy of our system. These results represent one of the first examples of AUVs autonomously taking decisions in a realistic and complex littoral surveillance scenario.

## I. INTRODUCTION

Nowadays, the capabilities of AUVs in terms of precise navigation, autonomy and endurance make them appealing assets for littoral surveillance and Anti-Submarine Warfare (ASW) scenarios. Traditionally, the task of ASW is a people-intensive activity and has been carried out by means of sensors such as sonobuoys and submarines or frigates with towed arrays [1]. Final objective is to infer from the large amount of collected data if a target is present in the area and to track it for its correct classification. Existing traditional approaches are expensive and manpower intensive.

The envisioned solution we have been pursuing at the NATO STO Centre for Maritime Research and Experimentation (CMRE) [2], [3] is the use of sensorised AUVs acting as autonomous mobile nodes in a multistatic network. AUVs can provide effective ASW capabilities at a fraction of the cost of traditional assets. In the CMRE multistatic sonar system, a sonar source (transmitter), which may be located on a stationary buoy or ship deployable, transmits a sonar

signal (ping) which reflects from objects and is collected by multistatic receivers (the AUVs towing an array in this case). Multistatic sonar systems have the potential to greatly increase ASW coverage and performance [4]. The possibility to use several sources and receivers generates different geometric distributions of source-target-receiver increasing the probability of detection and classification for a target. When the AUV receives an echo from the target, it builds a bearing/range contact that is fed into an on board tracker [5] based on a kinematic model of the target of interest. The tracker combines (spatially) related contacts over time to produce tracks.

A crucial point is the degree of autonomy of the vehicles, above all considered the limited communications bandwidth and range of the underwater sound channel that makes communication with the vehicles sparse and sometimes impossible. To be really effective, AUVs need to take decisions autonomously on the basis of the acquired data and of the evolving tactical scene.

In particular, data-driven navigation strategies [6], [7], [8], [5], [9] in which the AUV modifies its path based on the data collected during the mission, have the potential to increase the overall mission performance if compared to the pre-designed tracklines traditionally used in oceanographic/military applications [10].

We have recently designed and successfully tested at sea a non-myopic, receding horizon algorithm [3], [11]. The algorithm solves a sensor management problem [12] controlling the heading of the AUV to minimize the expected target position estimation error of a tracking filter by considering a future planning time horizon. The AUV actions can indeed better achieve the overall objectives by considering the evolution of the tactical scene in the future. Minimizing this error is typically of the utmost interest in target state estimation since it is one way of maintaining track. A candidate track is assumed being produced by the target and is used in the optimization. The AUV has therefore to select tracks likely being target-generated.

ASW scenarios are typically complex from the detection/-tracking point of view. The target may not be observable for long time due to the particular sound speed profile or low probability of detection. Several false tracks are usually simultaneously present and may last for several pings and finally the presence of ambiguous tracks (due to the port-starboard ambiguity of contacts in line arrays) increases the number of tracks of possible interest. Only the most interesting tracks should be investigated without wasting time and energy to optimize tracks not target related.

Gabriele Ferri, Andrea Munafò, Ryan Goldhahn and Kevin LePage are with the Research Department, NATO Centre for Maritime Research and Experimentation, Viale San Bartolomeo, 400, 19126 La Spezia (SP), Italy [Gabriele.Ferri@cmre.nato.int](mailto:Gabriele.Ferri@cmre.nato.int)

In this work we present an adaptive, data driven Mission Management Layer (MML) running on board the vehicles managing all the phases of the AUV missions. The MML receives the tracks and contacts produced by the signal processing chain, takes decisions in real-time on which tracks are interesting to be prosecuted and commands the vehicle Control Layer operations.

First of all, a metric is needed to quantify the quality of a track. The track quality can be defined as the probability of existence of the target corresponding to the track. To address this, we propose in this work a track scoring method based on the quality of the measurement-to-track associations. The method uses a model of the acoustics and the kinematic features of the target and does not need the knowledge of often difficult to estimate parameters such as the probability of detection. The real-time produced track score can then be used to classify the tracks to select which ones are interesting to be prosecuted by the non-myopic optimizer.

The MML manages all the phases of an ASW mission: exploration/surveillance of the area, disambiguation between a track and its ambiguous when one confirmed track is present, optimization of a confirmed track and target reacquisition when a track breaks. A compromise is found between the *exploration* of the area and *exploitation* of target cues. Only the most interesting tracks are prosecuted to avoid wasting time/energy in pursuing tracks not target-generated. These features are key points for an effective use of data-driven behaviours in real ASW scenarios. Our mission management approach pushes towards the full autonomy of our system providing the AUV the capability of adapting its actions to the current tactical situation. The proposed architecture is implemented in C++ on CMRE OEX vehicles, using the MOOS-IvP middleware. We present and discuss results from sea trials (REP14 Atlantic) demonstrating the effectiveness of our approach. These results represent one of the first examples of AUVs autonomously taking decisions in a realistic, complex littoral surveillance scenario.

## II. ALGORITHM DESCRIPTION

In this section we will start by describing the adopted target dynamics model. Then we will introduce and describe the track scoring index and the on board track classification which constitute the basis for the decision making process. Finally, the MML will be detailed in Sec. II-E.

### A. Target dynamics and tracks

A discrete-time model is assumed to describe the target dynamics with the sampling time  $\Delta$  being the pulse repetition interval of the acoustic source. The state vector at time  $k$  is defined as  $\mathbf{x}_k = [x_k, \dot{x}_k, y_k, \dot{y}_k]^T$ , consisting of  $x$ - $y$  coordinates with relative velocities with respect to an Earth fixed reference frame. The selected model assumes the target moving with a nearly-constant velocity [13]. A track is composed of a state vector representing the mean values of the estimate of the target position/speed and a covariance matrix  $\mathbf{P}$  representing the errors relative to this estimate. In the nearly-constant velocity model we assume the target

is navigating at a constant speed. So, the state evolution is described by the following:

$$\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \mathbf{w}_{k-1} \quad (1)$$

where  $\mathbf{F}$  is the state transition matrix and  $\mathbf{w}_k$  is a zero-mean white Gaussian sequence with covariance matrix  $\mathbf{Q}$  [13].

### B. Track scoring

Tracks are one of the most important driving factors for the AUV to take autonomous decisions. The ASW scenario is challenging from the tracking point of view. Several clutter-generated tracks may be simultaneously present. Some of these tracks may also be persistent and last for several pings. In addition, the target may not be observable for some time due to particular sound speed profile conditions or low probability of detection. In addition, the presence of false tracks due to the port-starboard ambiguity exacerbates the problem.

A measure is therefore needed to determine how interesting a track is. This should lead to a way of classifying tracks as generated by a target of interest, as being ambiguous or generated by clutter. Furthermore, having this information after few pings since the track creation would be critical for an effective planning of early AUV maneuvers. This kind of measure would help the AUV to select the tracks of interest to prosecute and would offer a guide on what to do once the tracks break.

This problem pertains to the track management and has been widely addressed by the tracking research community [13], [14], [15]. Track management is the decision process related to track generation, confirmation and termination. In general, these decisions are taken based on the total number of measurement associations, length of no association sequence, total lifetime of the track in question, and at least  $M$  detections out of  $N$  time steps logic [16], [15]. These approaches, although very popular in the community, do not take into consideration the quality of the measurement-to-track associations, which potentially brings additional useful information to support the decision process. A track target-originated is indeed more likely to have better measurement-to-track associations quality than a false track. Some approaches have therefore been proposed either for assignment [15] or for probabilistic data associations [17], [18] providing some measures of the quality of the tracks. These approaches use measures of the quality of measurement-to-track association together with estimates of the probability of detection ( $Pd$ ), probability of false alarm ( $Pf$ ) and the gating probability ( $Pg$ ) to assess the quality of a track (usually computed via Markov chains [15]).

However, in our underwater scenario, these parameters cannot be accurately estimated. The insufficient knowledge of different environmental clutter characteristics (causing difficulties in a good estimate of  $Pf$ ), the inaccurate knowledge of the acoustic propagation and target depth/heading (making the estimate of an accurate  $Pd$  challenging) motivates other approaches. Possible approaches involving information theory arguments can be pursued such as that proposed in

[19] in which an infinite Hidden Markov Model is used to classify tracks through differences in the entropy distribution of detections associated with the respective tracks.

In this work, we assume the *track quality* as being the probability of existence of the target corresponding to a track [15]. We propose a scoring to quantify it, based on the kinematic features of the target, a model of the physics of the acoustics and on the quality of measurement-to-track associations. The score takes into account the history of the tracks and can be used to classify them in different categories. Specifically the new tracklets produced by the on board tracker are analyzed by considering the associated contacts. At each ping, a scoring value is computed for the tracklet. That is for the track  $i$  at time  $k$

$$I_k^i = 1 + \alpha A_k^i + \beta \delta_k^i \quad (2)$$

where  $A_k^i$  is a quantity proportional to the quality of measurement-to-track association (if at that ping some association has occurred) which will be defined later and  $\delta_k^i$  is equal to 1 if an association both with one FM (Frequency Modulated) and a CW (Continuous Wave) contact has occurred at the same ping and 0 otherwise;  $\alpha$  and  $\beta$  are two weighting factors. We have noted that an association with the track of both an FM and CW contact at the same ping is a good indicator of the existence of a target originating the track.

To measure the quality of measurement-to-track associations, at time  $k$ , we start first defining for each track the residual covariance matrix [20] defined as

$$\mathbf{D}_k = \mathbf{H}\mathbf{P}_k^-\mathbf{H}^T + \mathbf{R}_k \quad (3)$$

where  $\mathbf{H}$  is the output matrix of the system, in our case  $\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$ ,  $\mathbf{P}_k^-$  is the propagated covariance from the step  $k-1$ , that is  $\mathbf{P}_k^- = \mathbf{F}\mathbf{P}_{k-1}^-\mathbf{F}^T + \mathbf{Q}$  and  $\mathbf{R}_k$  is the covariance error matrix of the measurement. With this, we compute the normalized scalar distance function

$$d_k^2 = \mathbf{e}_k^T \mathbf{D}_k^{-1} \mathbf{e}_k \quad (4)$$

with  $\mathbf{e}_k = [\mathbf{z} - \mathbf{x}_k]$ , being  $\mathbf{z}$  the  $x$ - $y$  measurement vector and  $\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1}$ . We then compute  $A_k^i$  as a function of  $d_k^2$ . For each track  $i$ , we are now able to compute  $I_k^i$ . The track scoring  $S_k^i$  is then obtained by summing the computed  $I_k^i$  at each ping, that is

$$S_k^i = S_{k-1}^i + I_k^i \quad (5)$$

The measurement covariance matrix  $\mathbf{R}_k$  is computed by using a procedure detailed in [21], [3]. An acoustic model [22] is used to estimate the SNR of the contacts associated to the track; the SNR is then used to compute the acoustic measurement uncertainties (on bearing and on arrival time) which are needed to compute the bistatic measurement error [23].

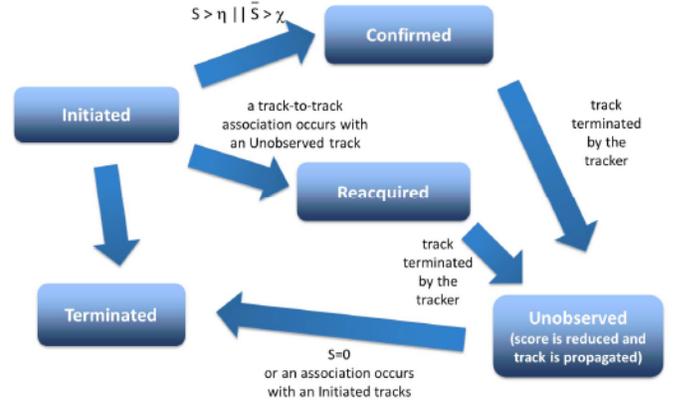


Fig. 1. Track classification scheme and transition between the different classes.

### C. Track classification

The proposed score is used for the real-time on board classification of the produced tracks. This is the basis for AUV decision making. The track classification scheme is shown in Fig. 1. A track can be classified as:

- Initiated.
- Confirmed.
- Unobserved.
- Reacquired.
- Terminated.

*Initiated* tracks are the new tracks produced by the tracker. If one of these tracks breaks, it is considered *terminated* by the MML and not considered any more. If the scoring  $S_k^i$  meets some conditions, specifically if the value of the score or if a measure of its increment in time become higher than certain thresholds (see the next section for details about the thresholds), the track  $i$  becomes *confirmed*. *Confirmed* tracks are considered candidates to be prosecuted by the AUV. If one *confirmed* track is terminated by the tracker, it becomes *unobserved*. *Unobserved* tracks are propagated and a track-to-track association is attempted [14] with the new *initiated* tracks produced by the tracker. The score is also reduced at each ping. If the score reaches 0, the track is *terminated*. Otherwise, if the association succeeds, the *initiated* track associated with the *unobserved* one becomes *reacquired*, while the *unobserved* is terminated. The *reacquired* tracks are treated as the *confirmed* ones as regards the transition to other states. They are considered worth of being investigated since likely generated by the same target which had originated a previously *confirmed* track.

It remains to define how to set the thresholds.

### D. Thresholds selection

A suitable threshold on the scoring needs to be defined. This is a key point to identify interesting tracks to be further investigated. By analyzing historical data, we realized that tracks originated by a target are characterized by two features: high scores (track persistence) and a high value of the increment of the scoring in time (good quality associations).

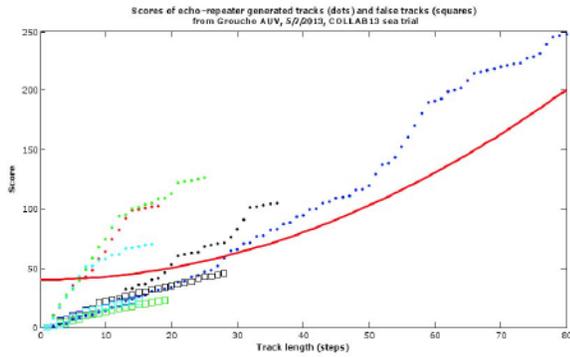


Fig. 2. Computed scoring with tracks generated by the echo-repeater (dots) and clutter-generated (squares). The adopted threshold is visible in red. The tracks have been produced by Groucho AUV on 5/7/2013 during COLLAB13 trial. On the  $x$  axis, each step represents the production of some contacts by the signal processing chain. In our system, each ping corresponds to two steps: generation of FM and CW contacts.

This is clear from Fig. 2 in which the scores of tracks produced by the Groucho AUV during COLLAB13 trial are shown. The tracks generated by the echo-repeater (used in the reported experiment to simulate a real target) are represented with dots, while the longest clutter-generated tracks of the mission are represented with squares. In the figures each step on the  $x$  axis represents the instant of production, during a track life, of the contacts by the signal processing chain. In our system, each ping corresponds to two steps: generation of FM and CW contacts. It is evident how, in general, the tracks originated by a target have a higher score and a higher increment of the scoring in time. This is due to the higher number of good associations in the target-related tracks causing a larger increase of the scoring. For these reasons, we define the parabolic threshold  $\eta$  visible in red in the figures to discriminate the two classes of tracks.

For an early identification of interesting tracks we also consider another condition on the increment in time of the score. A moving time window is considered on which the increments of the scoring are computed between two successive computation steps. The median of the computed values is chosen to represent the score variability over the time of the window. The resulting quantity,  $\bar{S}$ , is compared with a threshold  $\chi$ . If  $\bar{S} > \chi$  the track becomes *confirmed*. From Fig. 3 it is evident how the target-generated tracks are characterized by a larger increase of the scoring. Time periods of quick increasing of the score can cause an early confirmation of a track even if the value of the score does not reach the  $\eta$  value.

**E. Mission Manager Layer: description**

The MML state diagram is shown in Fig. 4 and is based on four operative states: *exploration*, *disambiguation*, *prosecution* and *reacquisition*. The mission starts in the explorative/surveillance phase to clear the patrolled area. If some tracks are judged candidate for prosecution, the MML takes the decision to investigate them. The AUV starts maneuvering to break possible ambiguous tracks (*disambiguation* state) and to select the most interesting one. Then,

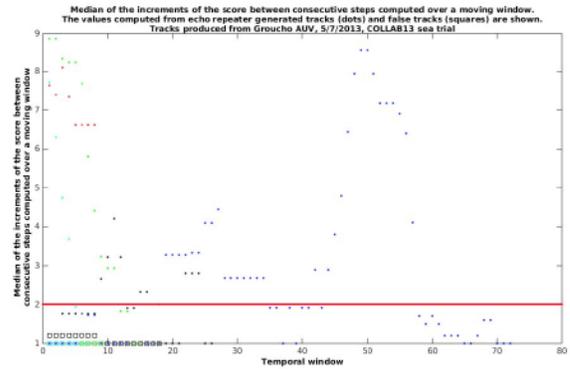


Fig. 3. Median of the increments of the score between the consecutive steps over a moving time window. Tracks generated by the echo-repeater (dots) and clutter-generated (squares) are shown. The selected threshold,  $\chi$ , is shown in red. The tracks have been produced by Groucho AUV on 5/7/2013 during COLLAB13 trial. A larger increment in time of the score is a good clue of a track generated by the target.

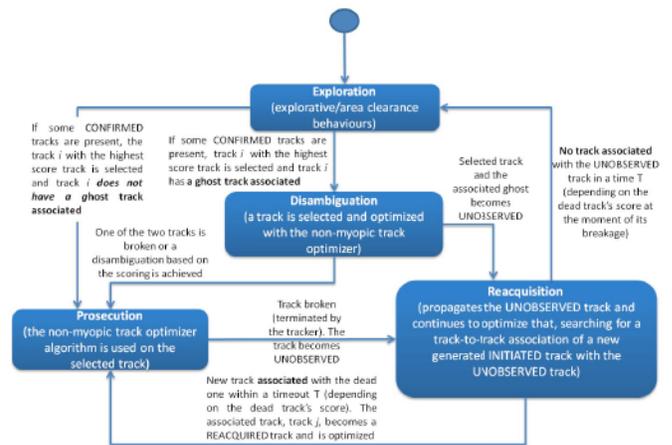


Fig. 4. MML state diagram.

it switches to (*prosecution*) in which the selected track is prosecuted until its final classification. If the track breaks, the AUV attempts to reacquire it by associating new-born tracks with a propagation in time of the broken one. If this happens, the AUV optimizes the associated track, otherwise the AUV switches back to the exploration. The current operative state defines the behaviours active to control the AUV. We describe in the next sections the actions carried out in each operative state. Specifically, the described behaviours associated to each state are those used in REP14 Atlantic and COLLAB-NGAS14 sea trials. This represents one possible configuration. The MML is a general framework and other behaviours can be selected to be active in each state. In the following the operative states are described in detail.

1) *Exploration*: in the *exploration* state, the AUV navigates following pre-fixed racetracks constituted of four waypoints and set by the mission designer on the basis of the mission objectives and constraints. During the navigation, the on board signal processing software processes the echos and creates tracks. The exploration continues until some of the tracks become *confirmed*.

When this happens, the *confirmed* track with the highest

score is selected. Two cases are possible: the track may not or may have an associated ghost track. In the first case, the MML switches to *prosecution* to optimize the selected track. In the second, the MML switches to *disambiguation*, since it is not known which is the real track to be pursued.

2) *Disambiguation*: the AUV starts optimizing the highest score track by using the non-myopic optimization algorithm previously described [21]. At this point, the choice of the track to be prosecuted is arbitrary. The aim is to exploit the AUV movement to discriminate the true from the ambiguous track. The false track can break due to the fact the contacts are not associated to it since the movement of the AUV makes the contacts not compatible with the ambiguous track. Secondly, the track scoring of the true track will increase more than those of the ambiguous track since the associations with the true track will be of “better” quality [24]. In this case, we could discriminate between the two tracks by checking the two scores.

If a successful disambiguation is achieved in either mode, the MML can switch to the *prosecution* state. It may also occur that, during the optimization maneuvers, the tracks break and become *unobserved*. In this case MML switches to *reacquisition* for an attempt of reacquiring the broken tracks.

3) *Prosecution*: in the *prosecution* state, the selected *confirmed* track is prosecuted by using the non-myopic algorithm [3]. The AUV continues the prosecution until the track breaks becoming *unobserved*. In this case, the MML switches to *reacquisition* to reacquire the target.

4) *Reacquisition*: during the *reacquisition* phase, the track which has become *unobserved* is propagated into the future and the AUV proceeds in its prosecution by using the non-myopic optimization algorithm. Specifically, the state of the track is propagated into the future according to  $\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1}$ , while  $\mathbf{P}_k = \mathbf{F}\mathbf{P}_{k-1}\mathbf{F}^T + \mathbf{Q}$ , is used to propagate the estimate error covariance matrix. The aim of the prosecution of the *unobserved* track is to drive the AUV in favourable positions to ease new target detections to lead to its reacquisition.

During its navigation, the AUV tries to associate one of the the new-born *initiated* tracks with the propagated *unobserved* track [14]. This leads to a track-to-track association problem to decide if one *initiated* track and the *unobserved* are generated by the same target.

Track association consists of two steps: computing a table of association metrics and selecting the best association hypothesis, usually by some assignment algorithm. In our case we use a method based on the approach presented in [14]. The optimal test requires using the entire data base (the sequences of measurements that form the tracks) through the present time and is not practical. In view of this, the used approach uses a track-to-track association test based only on the most recent estimates from the tracks. The method was selected due its simplicity of implementation and low computational power requirements. Specifically, an association test is carried out by using the most recent covariance and state of the *unobserved* propagated track, and the same quantities of the *initiated* tracks produced by the

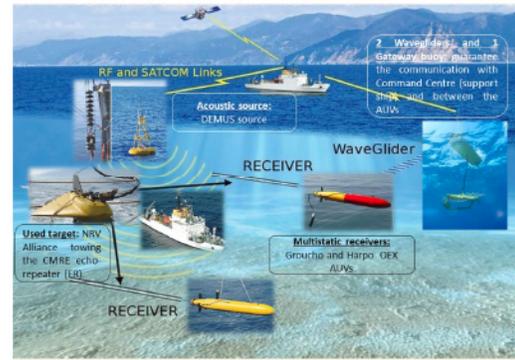


Fig. 5. CMRE cooperative ASW multistatic network deployed in REP14 Atlantic and COLLAB-NGAS14 sea trials.

tracker. Results on historical datasets show the effectiveness of this approach. Details can be found in [24].

The timing of the reacquisition is ruled by the value of the score of the track at the moment it becomes *unobserved*. The score value is decreased at each Pulse Repetition Interval (PRI) until an association occurs or it becomes zero. In the case an association is decided, the MML classifies the associated *initiated* track as *reacquired* initializing its scoring on the basis of the current value of the score of the *unobserved* track. That track is then selected to be pursued, and MML switches to the *prosecution* operative state. In this case, the *unobserved* track has been reacquired and the *reacquired* one represents its natural continuation worth of being further investigated. If the *unobserved* track scoring reaches zero and no association has occurred, the MML switches back to the *exploration* state. The track is considered definitely lost and the vehicle comes back to explore its area of interest to wait for new interesting tracks. The track scoring influences the time  $T$  dedicated to the reacquisition since a higher score is considered an indicator of a track that is more likely being target-generated and therefore more time is dedicated for its reacquisition.

### III. EXPERIMENTAL RESULTS

We validated the MML and the track scoring at sea during the REP14 Atlantic (July 2014) and COLLAB-NGAS14 (October 2014) sea trials. In this section, after briefly describing the CMRE cooperative ASW multistatic network, we present results of the use of MML at sea during REP14 Atlantic.

#### A. CMRE cooperative ASW multistatic network

The CMRE multistatic network used during the REP14 Atlantic and COLLAB-NGAS14 trials is shown in Fig. 5.

The source used was the Deployable Experimental Multistatic Undersea Surveillance System (DEMUS) [1]. The source is bottom-tethered and was not moved during the experiments.

The two CMRE Ocean Explorer (OEX) AUVs were used as the moving assets in the CMRE cooperative ASW system. These vehicles are approximately 4.3 m long and 0.53 m wide. The endurance depends on the payload. They can reach 16 hrs of operations at a speed of 1 m/s. AUVs communicate

between each other and with the other nodes of the network via a 7/17 kHz Evologics [25] low-frequency modem.

The OEX AUVs were both deployed with the BENS slim towed array (SLITA) [26]. The arrays are deployed approximately 3.5 m behind the vehicle. The BENS arrays have three nested sets of 32 hydrophones each. The hydrophone set used during the sea trials was optimized for frequencies up to 3.47 kHz (0.21 m spacing). During the described experiments, both vehicles suffered from the inability to discriminate the starboard from port side measurements.

All the assets were deployed from the NATO Research Vessel (NRV) Alliance. The vessel operated as the command and control centre during the experiments. Furthermore, it towed the echo-repeater to act as the simulated target during the experiments. The echo-repeater recorded the waveforms received following the DEMUS transmissions and then re-transmitted the recorded signals with a user-specified amplitude gain after a user-specified delay. During the experiments described in this document, the echo repeater re-broadcast the incoming sonar signal with a tunable gain (e.g. 15 or 20 dB) over the received level. This gain serves as a substitute for the target sonar cross-section or reflectivity. Further details can be found in [11], [24].

The MML was implemented and integrated in the control system running on the CMRE OEX vehicles. The software architecture is based on MOOS-IvP [27]. MOOS-IvP is an open source C++ framework for providing autonomy to robotic platforms, in particular marine vehicles. MOOS-IvP is based on the publish/subscribe paradigm: a community of processes subscribes to receive and publish variables from/to a database (MOOSDB). For the management and control of vehicles, the MOOS framework works according to the backseat-driver: MOOS processes managing the mission run on the backseat computer receiving data from/issuing commands to the frontseat computer. The IvP Helm [27] is a MOOS application that enables behaviour-based autonomy. Behaviours can run simultaneously and can be grouped into behaviour sets, which are active based on certain conditions. Each behaviour is given a weight which is defined at mission start but may also be adjusted dynamically during the mission by on-board processes. IvP, a mathematical interval programming technique, combines the objective functions produced by active behaviours to determine a globally optimal solution for each domain [27]. The IvP Helm, typically running four times per second, is able to reconcile the different active behaviours to produce the commands for the frontseat controller, specifically speed, heading and depth commands. The MML controls, according to the taken decisions, the vehicle Control Layer (constituted by the IvP Helm with the different behaviours, e.g. racetrack, non-myopic optimization etc.). In the reported experiments, for instance, during the *exploration* phase a racetrack was executed. The Control Layer, by receiving the tasks to be fulfilled by the MML, is in charge of managing the different behaviours to control the vehicle operations. This layered architecture decouples the planning/deliberation activities managed by the MML from the executive actions managed by the Control Layer.

In our architecture, the Functional Layer is represented by the frontseat where the vehicle autopilots and low level control algorithms run.

### B. Results of Harpo AUV controlled by MML at sea during REP14 Atlantic

REP14 Atlantic sea trial was held in the Atlantic Ocean, off the coast of Lisbon, Portugal, in July 2014. We report and discuss here the results of the MML running on Harpo AUV during a trial at sea on 10 July 2014. In this experiment, the echo-repeater towed by the NRV Alliance, moving at a speed of 2 m/s, was used as a reproducible and controllable target.

The experiment set-up is visible in Fig. 6. The DEMUS was used as the source and is identified by the red circle and the TX label. The path of the target is shown with a red line. The AUV path is shown in green and the current position is indicated by the RX label. The black dots represents FM contacts while the magenta ones are the CW. Squares are contacts associated to a certain track: in black the associations of FM contacts while in magenta the associations of CW measurements.

The AUV started its mission by moving along a pre-designed racetrack at a speed of 1 m/s (see Fig. 6). The AUV is heading toward south-east with a heading angle of 148°. At ping 88 the MML was enabled via an acoustic message from the NRV Alliance. The scoring of track 408 increases rapidly due to FM and CW associations of good quality (for instance a good CW association is shown in Fig. 6). At ping 95 (see Fig. 7) track 408 becomes *confirmed*. The MML switches to *prosecution* selecting the track 408. The track 408 has a ghost track associated, the track 419. MML, however, correctly selects the track 408 since it has higher score than the other. In this case, this is due to the fact that the ambiguous track starts outside the patrolled area where the score is not updated. Once in *prosecution*, the AUV maneuvers by turning to south (Fig. 7). Track 408 then breaks (Fig. 8) and is propagated (magenta line) while the AUV tries to reacquire it. To do that, the propagation of track 408 is optimized to drive the vehicle in favourable locations for a target re-detection. This happens at ping 101. Here track 488 is associated with the propagation of track 408. The AUV has therefore reacquired the target and prosecutes the new *reacquired* track switching the operative state to *prosecution*. The optimization on the reacquired target proceeds until ping 110 when the track breaks (Fig. 9). Finally, in Fig. 10 the vehicle is shown trying to reacquire the track 488 by executing a turn eastward moving the estimated target position at the array broadside. This experiment shows the capability of the proposed MML to select the most interesting tracks, filtering out most of the false tracks and allowing an effective use of the non-myopic optimizer. At the same time, the target reacquisition mechanism provides a guide to the AUV on how to behave when the target becomes not detectable and the associated track breaks. These situations are strongly dependent on the target SNR and the current acoustic channel situation. Low target SNR

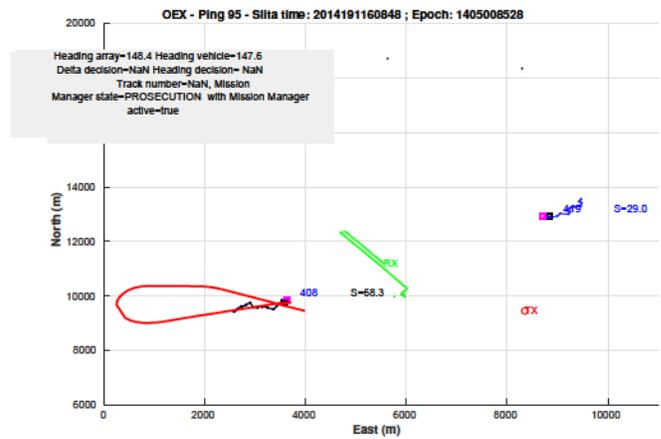


Fig. 6. Data from Harpo AUV, in the mission of 10 July 2014 during REP14 Atlantic sea trial. Position of the DEMUS source (red circle and TX label), trajectories of the target (red line) and of the receiver AUV (green line and RX label). The contacts are shown as black points (FM) and magenta points (CW). Points associated to a track are represented by a black and magenta square, if they are respectively FM or CW contacts. Tracks are also plotted with their number and the computed score. The vehicle sails along the pre-designed tracklines towards south-east in the MML *exploration* operative state. The magenta line is related to the track with id 327 which is propagated after being declared *confirmed*. At that time the MML was not active, but the track had been correctly scored and classified.

and poor acoustic propagation conditions can lower the  $P_d$  causing the target becoming unperceivable. In general, this is the usual situation when a low SNR target is tracked. A target reacquisition strategy is therefore necessary.

IV. DISCUSSION AND CONCLUSION

We investigated how to improve the decision making of AUVs for their effective use in a multistatic ASW network.

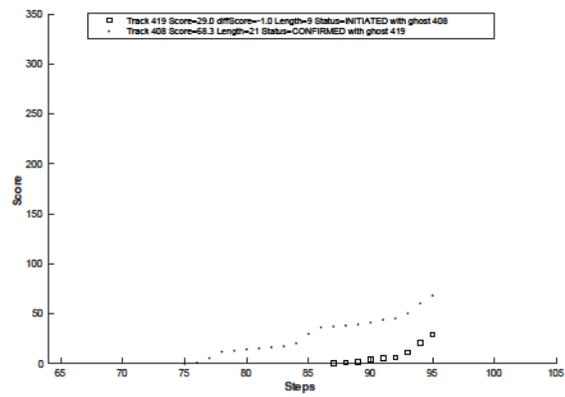
In data-driven approaches the AUV modifies its path based on the data collected during the mission to better achieve the mission objectives. This kind of strategies has been demonstrated [3] capable to increase the efficiency of AUV missions.

It is not trivial in ASW scenarios to select the tracks to be prosecuted by these algorithms. ASW scenarios generally present a large number of tracks simultaneously present and the target, especially if characterized by a low SNR, becomes unobservable for long time.

To address these problems, we proposed an adaptive, data driven Mission Management Layer (MML) running on board the vehicles managing all the phases of an AUV mission. The MML receives the tracks and contacts produced by the signal processing chain, takes decisions in real-time on which tracks are interesting to be prosecuted and commands the vehicle control layer operations. The MML manages all the phases of an ASW mission: exploration/surveillance, tracks prosecution and target reacquisition, finding a trade-off between the exploration of an area and exploitation of cues related to targets (only tracks likely being produced by a target are optimized).

A metric to quantify the quality of a track has been proposed. The proposed track scoring method, based on the

(a) Ping 95 - Positions of the AUV, target, contacts and tracks.



(b) Ping 95 - Track scoring for the present tracks.

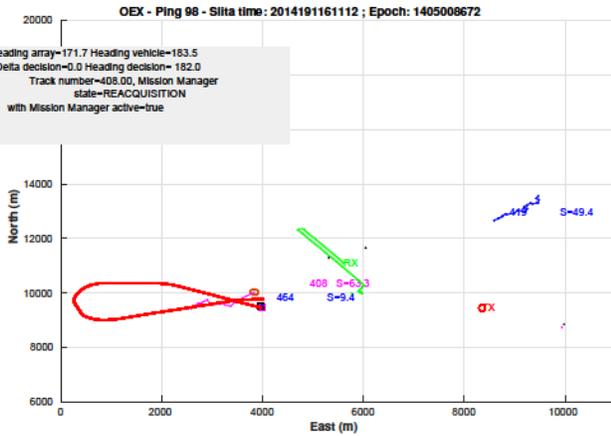
Fig. 7. (a) The track 408 is confirmed and the AUV starts optimizing it. (b) Track scoring for the present tracks.

quality of the measurement-to-track associations, does not need the knowledge of often difficult to estimate parameters such as the probability of detection. The real-time produced track score is then used to classify the tracks to select which of them have to be prosecuted.

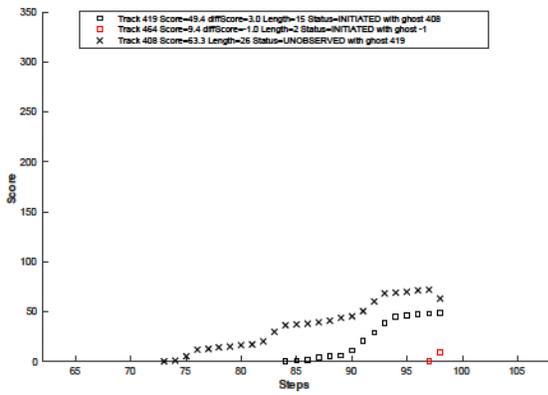
These features are key points for the effective use of data-driven behaviours in real ASW scenarios. Our mission management approach pushes towards the full autonomy of our system providing the AUV the capability of adapting its actions to the current tactical situation.

Results from sea trials (REP14 Atlantic and COLLAB-NGAS14) demonstrate the effectiveness of our approach. These results represent one of the first examples of AUVs autonomously taking decisions in a complex, littoral surveillance scenario.

Difficulties may arise in setting the thresholds. In general, the thresholds need to be set by considering the faced environment in terms of present sound speed profile, reverberation, clutter, etc. In our experiments, historical data and the data collected from the first AUV missions of a sea trial are used to set the thresholds. The selected values then remained the same for the rest of the exercise. In our experience, the experimental results show that the situation



(a) Ping 98 - Positions of the AUV, target, contacts and tracks.



(b) Ping 98 - Track scoring for the present tracks.

Fig. 8. (a) The track 408 becomes *unobserved*. The AUV maneuvers to reacquire the target prosecuting the propagation of track 408. (b) Track scoring for the present tracks. The score of track 408 decreases during the target reacquisition maneuvers.

from a track score perspective does not change evidently from day to day during a sea trial. This helps us in the setting of suitable thresholds valid for the whole sea trial based on the data collected in the vehicle missions of the first days.

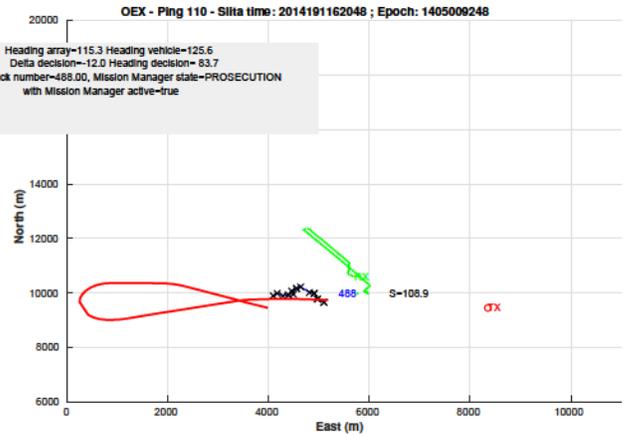
Future work will investigate methods for the AUV to automatically set the threshold used in the track scoring according to the encountered scenario to make the scoring system adapt to the different encountered environments.

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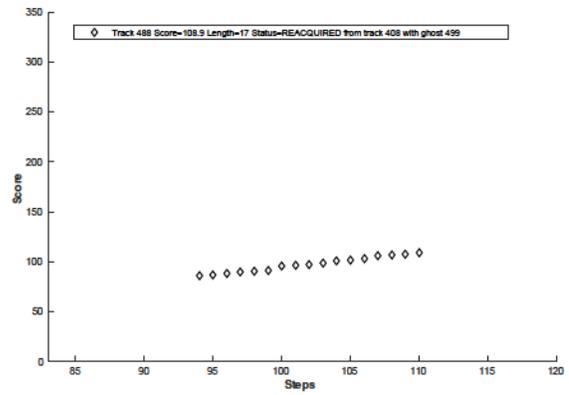
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(a) Ping 110 - Positions of the AUV, target, contacts and tracks.



(b) Ping 110 - Track scoring for the present tracks.

Fig. 9. (a) The track 488, which has been associated at ping 101 with the *unobserved* track 408, is prosecuted and the AUV maneuvers to keep the target at a favourable bearing with respect to the array. (b) Track scoring of the *reacquired* track 488.

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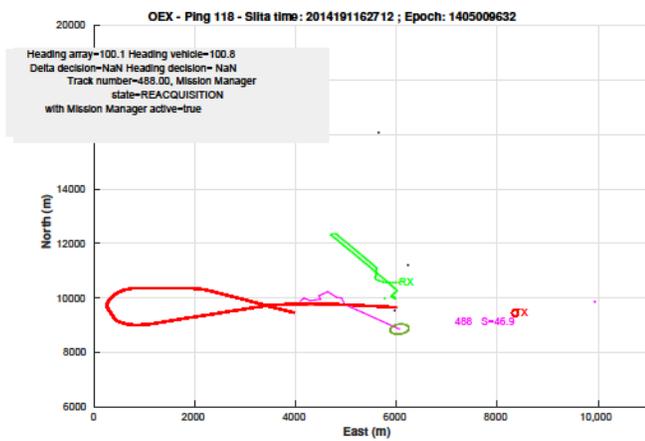
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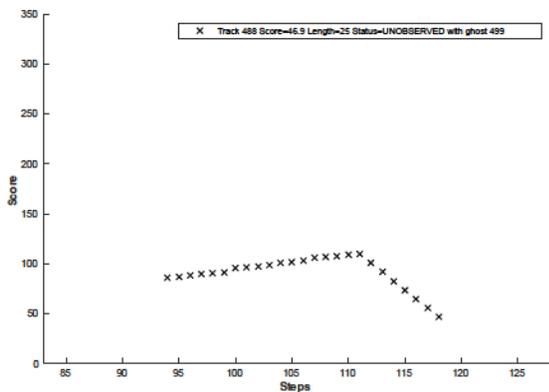
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(a) Ping 118 - Positions of the AUV, target, contacts and tracks.



(b) Ping 118 - Track scoring for the present tracks.

Fig. 10. (a) At ping 111, the track 488 becomes *unobserved* and the AUV starts to reacquire it. Harpo maneuvers to position itself in a favourable position to increase the  $P_d$  and reducing the estimated tracking error. (b) Scoring of the *unobserved* track 488 decreasing during the target reacquisition

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# Document Data Sheet

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<i>Author(s)</i> Gabriele Ferri, Andrea Munafò, Ryan Goldhahn, Kevin LePage		
<i>Title</i> Towards fully autonomous underwater vehicles in ASW scenarios: An adaptive, data driven AUV mission management layer		
<i>Abstract</i> <p>We present an adaptive, data driven Mission Management Layer (MML) to manage the phases (surveillance, track prosecution and target reacquisition) of the mission of AUVs operating as receiver nodes in a multistatic network for littoral surveillance. Among the tracks produced by the on board tracker, the MML selects those which are likely originated by a target. The MML then issues commands to the vehicle Control Layer to trigger data-driven optimization behaviours to prosecute these candidate tracks. Selecting few candidate tracks is indeed crucial since the addressed scenario usually presents many tracks hence resulting challenging from the tracking point of view. To select the candidate tracks, a metric is introduced to quantify their quality. It is based on the kinematic features of the target, on an acoustic model and on the quality of measurement-to-track associations. By selecting a limited subset of produced tracks, the MML can improve the benefits of using data-driven behaviours activating them only on interesting cues and reducing the time wasted to optimize tracks not related to a target. This aims at achieving a balance between the surveillance of the area of interest and exploitation of target cues (tracks). These features are essential for improving the overall mission performance and for an effective AUV decision making in realistic conditions. We present results from sea trials demonstrating the effectiveness of our approach and how the proposed MML can represent a step forward towards the full autonomy of our system. These results represent one of the first examples of AUVs autonomously taking decisions in a realistic and complex littoral surveillance scenario.</p>		
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