SCIENCE AND TECHNOLOGY ORGANIZATION
CENTRE FOR MARITIME RESEARCH AND EXPERIMENTATION

Reprint Series **CMRE-PR-2019-056**

Cooperative robotic networks for underwater surveillance: an overview

Gabriele Ferri, Andrea Munafò, Alessandra Tesei, Paolo Braca, Florian Meyer, Konstantinos Pelekanakis, Roberto Petroccia, João Alves, Christopher Strode, Kevin LePage

June 2019

Originally published in:

IET Radar, Sonar & Navigation, volume 11, issue 12, December 2017, pp. 1740-1761, doi: 10.1049/iet-rsn.2017.0074

About CMRE

The Centre for Maritime Research and Experimentation (CMRE) is a world-class NATO scientific research and experimentation facility located in La Spezia, Italy.

The CMRE was established by the North Atlantic Council on 1 July 2012 as part of the NATO Science & Technology Organization. The CMRE and its predecessors have served NATO for over 50 years as the SACLANT Anti-Submarine Warfare Centre, SACLANT Undersea Research Centre, NATO Undersea Research Centre (NURC) and now as part of the Science & Technology Organization.

CMRE conducts state-of-the-art scientific research and experimentation ranging from concept development to prototype demonstration in an operational environment and has produced leaders in ocean science, modelling and simulation, acoustics and other disciplines, as well as producing critical results and understanding that have been built into the operational concepts of NATO and the nations.

CMRE conducts hands-on scientific and engineering research for the direct benefit of its NATO Customers. It operates two research vessels that enable science and technology solutions to be explored and exploited at sea. The largest of these vessels, the NRV Alliance, is a global class vessel that is acoustically extremely quiet.

CMRE is a leading example of enabling nations to work more effectively and efficiently together by prioritizing national needs, focusing on research and technology challenges, both in and out of the maritime environment, through the collective Power of its world-class scientists, engineers, and specialized laboratories in collaboration with the many partners in and out of the scientific domain.

IET Radar, Sonar & Navigation

Special Section: Sonar Multi-sensor Applications and Techniques

Cooperative robotic networks for underwater surveillance: an overview

ISSN 1751-8784
Received on 21st February 2017
Revised 22nd May 2017
Accepted on 19th June 2017
E-First on 11th August 2017
doi: 10.1049/iet-rsn.2017.0074
www.ietdl.org

Gabriele Ferri[*1] ✉, *Andrea Munafò*[*2], *Alessandra Tesei*[1], *Paolo Braca*[1], *Florian Meyer*[3], *Konstantinos Pelekanakis*[1], *Roberto Petroccia*[1], *João Alves*[1], *Christopher Strode*[1], *Kevin LePage*[1]

[1]*NATO STO-Centre for Maritime Research and Experimentation (CMRE), Viale San Bartolomeo 400, 19127 La Spezia (SP), Italy*
[2]*Marine Autonomous & Robotic Systems (MARS), National Oceanography Centre, University of Southampton Waterfront Campus, European Way, Southampton SO14 3ZH, UK*
[3]*Laboratory for Information & Decision Systems (LIDS), Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, USA*
**Co-first authors.*
✉ *E-mail: gabriele.ferri@cmre.nato.int*

Abstract: Underwater surveillance has traditionally been carried out by means of surface and undersea manned vessels equipped with advanced sensor systems. This approach is often costly and manpower intensive. Marine robotics is an emerging technological area that enables the development of advanced networks for underwater surveillance applications. In contrast with the use of standard assets, these advanced networks are typically composed of small, low-power, and possibly mobile robots, which have limited endurance, processing and wireless communication capabilities. When deployed in a region of interest, these robots can cooperatively form an intelligent network achieving high performance with significant features of scalability, adaptability, robustness, persistence and reliability. Such networks of robots can be the enabling technology for a wide range of applications in the maritime domain. However, they also introduce new challenges for underwater distributed sensing, data processing and analysis, autonomy and communications. The main thrust of this study is to review the underwater surveillance scenario within a framework of four research areas: (i) underwater robotics, (ii) acoustic signal processing, (iii) tracking and distributed information fusion, and (iv) underwater communications networks. Progress in each of these areas as well as future challenges is presented.

1 Introduction

Undersea surveillance is the requirement to detect, localise and classify *targets* (e.g. divers, manned or unmanned vehicles) in an underwater area of interest using fixed or mobile heterogeneous sensors. Targets can either move, as for instance in the case of acoustic monitoring of cetaceans [1] and in anti-submarine warfare (ASW) applications [2], or be fixed, such as in the mine countermeasures (MCM) framework [3]. Hybrid scenarios, in which mobile or fixed targets may be encountered, are port protection [4, 5] or the protection of critical infrastructures [6].

To simplify the problem, the surveillance area is usually assumed to be of a fixed location. However, in the general case, there may be situations in which the area of interest is dynamic, as, for instance, in the case of an area around a high-value ship in navigation, which must be guaranteed free of menace [7].

Undersea surveillance is a challenging task. Light penetrates poorly in the ocean [8], and electromagnetic waves do not propagate well in seawater at wavelengths reasonable for target detection and surveillance [9]. While optical, electromagnetic (EM), magnetic and other means of undersea surveillance remain important and are the subject of continual improvement [10], *sonar*, which is based on the monitoring and transmission of sound underwater, is the generally superior sensing modality for a broad variety of applications. Sonar-based underwater surveillance relies on the processing of acoustic information, either that radiated by underwater noise sources of interest, i.e. passive sonar, or that reflected from underwater objects of interest, i.e. active sonar. Both approaches are limited in their performance due to a variety of reasons (see Section 3), including the number and the operational capabilities of the platforms that deploy them, the constraints imposed on the sonars by the platforms themselves, and the constraints imposed by the physics of the ocean environment on the sonars. Furthermore, underwater communications, commonly exploiting the sound channel, are unreliable and characterised by limited bandwidth and range [11], hence limiting the ability of the surveillance system to effectively share information.

Historically, one of the most studied underwater surveillance application is ASW. In a typical ASW scenario, a submarine, which manoeuvres in an attempt to evade detection, must be localised. Due to its dynamic and challenging nature, the ASW problem can be considered as a representative case study for the wider range of underwater surveillance applications. The different concepts and problems faced in ASW since the beginning of the twentieth century are common to other scenarios and solutions applicable to ASW can be borrowed, adapted, and eventually used in other applications.

Passive ASW is typically performed using marine patrol aircraft (MPA) and marine patrol helicopters (MPH) deploying passive sonobuoys, surface ships towed arrays, submarines with flank or towed arrays, or fixed installations of hydrophones such as the integrated undersea surveillance system network [12, 13]. All of these systems listen for the distinctive noises generated by targets as they operate in the ocean. While passive ASW has been for many years the preferred method of conducting ASW, ever-lower target signatures and higher ambient noise levels in many areas of operational interest have driven a renewed interest in active ASW. The state of the art in active ASW is based upon the deployment of active sonobuoys from MPA and MPH, the use of hull mounted and variable depth sonar (VDS) deployed from surface ships working in conjunction with towed arrays, dipping sonar deployed from surface-ship-based organic helicopters, and low-frequency active systems such as the surveillance towed array sensor system deployed from dedicated platforms [2].

Even though the capabilities of these systems are advanced, these platforms introduce operational constraints as well as constraints on the sensors they deploy. Persistent surveillance

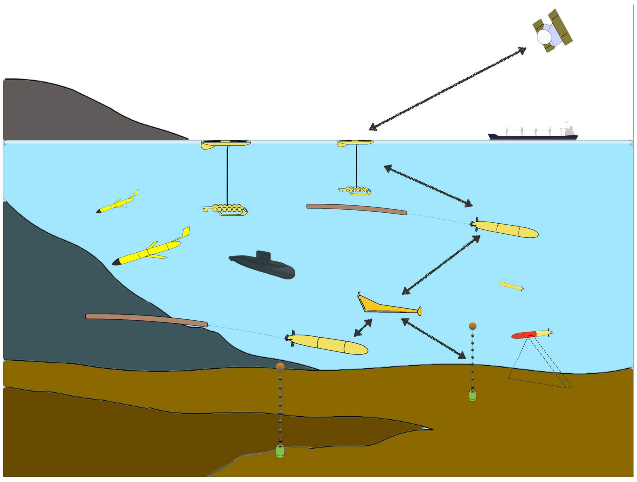


Fig. 1 *A sketch of the AOSN concept. A network of fixed sensors is integrated together with a fleet of heterogeneous AUVs, each one carrying some appropriate payload or sensors, and collecting data over survey tracks not reached by the fixed stations. This concept facilitates synoptic observations with an increased spatial resolution at potentially reduced cost with respect to traditional means (adapted from [16])*

cannot be guaranteed by aerial vehicles (MPA/MPH) due to their limited time on station. Conventional submarines need to surface to maintain their batteries and are often unable to be closely integrated into ASW task-force operations due to their inability or reluctance to engage in active transmission to maintain communications. Finally, ships deploying VDS and towed arrays impose limitations on their sensors [10], through radiated noise from the platform itself, flow noise when operating at speed and difficulties in deploying the sensors at the optimum depths due to the operational envelope of these complicated and heavy systems.

1.1 The rise of robotics in underwater surveillance

Recent advances in *marine robotics* suggest that maritime unmanned systems can be used to solve some of the problems identified above. Today's robots can guarantee persistent monitoring of an area at lower costs than traditional assets, complementing or substituting current solutions.

The idea of using autonomous robots or sensing units in ocean monitoring traces back to the early 1990s [14, 15], when the fast development of autonomous oceanographic instrumentation and communication systems encouraged the vision of highly integrated systems of autonomous oceans sampling networks (AOSN) (see Fig. 1). AOSN, composed of multiple and possibly low-cost units, can replace in a cost-effective way the traditional survey methods, with the additional benefit of providing synoptic data. The original AOSN concept was to have a network of fixed sensors integrated with a fleet of autonomous underwater vehicles (AUVs), each one carrying some payload or sensor, and collecting data over survey tracks beyond the range of the fixed stations. The key component of the AOSN concept was the AUV, through which synoptic observations could be obtained at potentially significantly reduced costs. At the time of the AOSN proposal, the available operational AUVs were designed for deep water geophysical surveys, accordingly to the needs of the oil and off-shore industries.

The technological evolution of the last decades has made small, relatively low-cost AUVs a reality: the available systems range from those employed for acoustic surveillance for military applications [7] to smaller, less powerful but longer endurance, oceanographic sensing units that can stay at sea for prolonged periods of time [17, 18] and to multi-purpose, mission-oriented assets [19]. The robotic research is now beyond this original idea, and the AOSN concept is included into an integrated system which includes aerial and aerospace units, with a reach-back capability towards the command and control (C2) centre able to monitor in real time the evolution of the system and to provide commands and updates to the network itself [20].

Surveillance and monitoring scenarios are amongst those where these new paradigms can be readily applied. Existing surveillance systems composed of statically deployed sensors, or based on the use of expensive and time-consuming ship-based operations, could be easily and effectively complemented with robotics platforms. Compared to traditional assets, these small, low-power, sensorised and mobile units have usually limited processing and communication capabilities, but when deployed in a spatially separated manner, they can be interconnected to form an intelligent *network* able to achieve high mission performance. Within this framework, nodes cooperate and make distributed decisions based on locally collected and/or communicated data. Static nodes collect data at fixed locations for extended time periods forming the backbone of *ad hoc* communication infrastructures. Mobile units build upon acquired data and use their mobility to extend the operational area and to adapt mission objectives to ever changing environmental and mission conditions, as well as to cover connectivity holes in the network and to avoid the presence of single points of failure. This results in the possibility for the network to efficiently adapt to evolving scenarios increasing its *reconfigurability*, *reliability* and *robustness*. A key aspect of a cooperative network lies in its ability to share data and information among its nodes. For underwater robotic networks, the key challenge is hence how to make effective use of the collected data and of the limited communication bandwidth in order to outperform traditional surveillance systems.

The use of cooperative robotic networks with a specific focus towards ASW applications has been recently demonstrated by the NATO STO-Centre for Maritime Research and Experimentation (CMRE) during a number of at-sea experiments [21–23], see Fig. 2. In the CMRE case [24], the robotic network embodies a multistatic active sonar system. It is composed of one or more active sources (transmitters), which transmit signals (pings). The sound, once reflected off some object, can be recorded by one or more receivers that are mounted on-board AUVs.

The operation of the vehicles is supported by WaveGliders [25], i.e. autonomous surface vehicles (ASVs) exploiting the wave energy to move, and by additional static buoys, which represent the backbone of an *ad hoc* communication and localisation infrastructure [23]. All nodes of the network are equipped with acoustic modems to exchange data. Finally, the NATO research vessel (NRV) alliance is used as an additional source and/or receiver, as well as C2. Using multiple sources and receivers, the CMRE network is able to enlarge its coverage while exploiting the different geometric distributions of source-target-receiver to increase the probability to receive a sonar echo that is originated by the target.

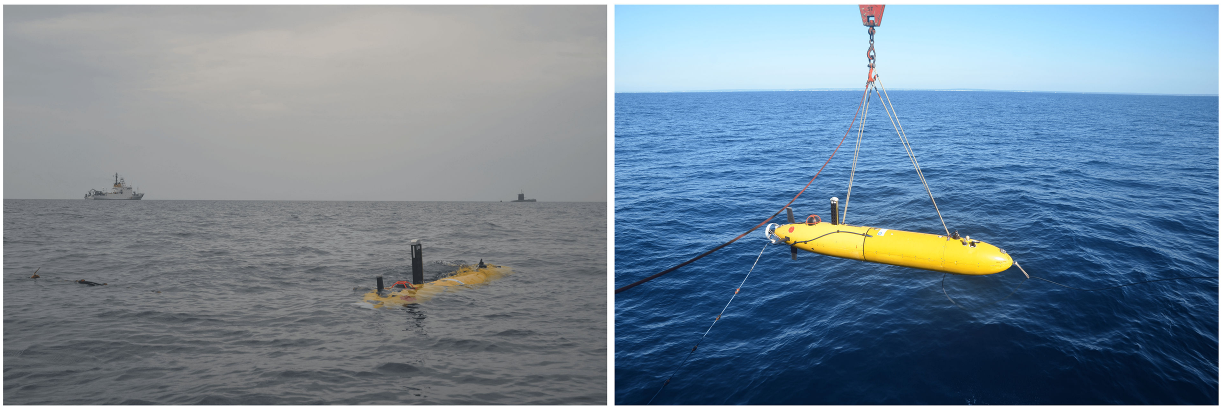
1.2 Underwater domain challenges

Several challenges must be addressed to realise and deploy underwater robotic networks in real-world applications:

- difficulties of underwater operations,
- lack of power and endurance,
- severely limited electromagnetic propagation for both sensing and communications.

To set up the discussion that follows in the next subsections, Table 1 summarises the main challenges for the deployment of underwater robotic networks. To provide a better context for the reader, the table also compares the specific issues as encountered in terrestrial/aerial domains.

1.2.1 Difficulties of underwater operations: Operating underwater requires that the vehicles are water tight and corrosion resistant and able to withstand increasing pressures. This results in a number of engineering challenges which must be met and further serves to increase the cost of these systems when compared to terrestrial solutions. Even the basic deployment and recovery of these vehicles can be challenging and it likely requires the employment of a sea going vessel with suitable lifting gear. This adds further costs to the system as a whole. As a result of such a



a *b*

Fig. 2 *NATO STO-CMRE Harpo OEX AUV during at-sea operations*
(a) Harpo OEX AUV acting as receiver in the CMRE network during LCAS16 trial. The NRV Alliance research vessel and a submarine involved in the trial are also visible, ***(b)*** Harpo during the deployment. The linear hydrophone array towed by the vehicle is visible (photo credit: Arjan Vermeij)

Table 1 Underwater domain challenges

	Terrestrial/aerial domain	Underwater domain	Challenges on signal processing	Challenges on robotics
Power	Combustion engines, batteries etc.	Battery dependent. Recharging difficulties	Array algorithms that trade power for efficiency	Mission duration, low speed
Hardware	Structural constraints only due to shape and material optimisation	Structural constraints due to high pressures and corrosion. Limitations for communications and signal processing (e.g. narrow bandwidth due to piezo transducers).no standards	Half-duplex networking	Propulsion, manoeuvrability, limited interoperability
Network Deployment	2D dense networks, mostly static nodes, possibility of infrastructures	3D sparse networks, possibility of multiple mobile nodes, fully *ad hoc*	Physical level and network design	Autonomy
GNSS signal	Yes	No	Difficult localisation and synchronisation	Localisation and navigation
Wave speed	3×10^8 m/s (light)	1500 m/s (acoustics), varies in space and time	High latency in communications protocols	Feedback latency for C2
Signal fading	Outage models known	Outage models unknown	Poor target detection, high false-alarm rates, low rate and unreliable communications	Autonomy, limited collaboration
Multipath	μs	ms – seconds		
Noise	Electronic, non-dynamic	Environmental, very dynamic		
Freq/band	High	Low		
Bitrate	Mbps	<15 kbps (acoustics)		
Costs	Easy to deploy multi-agent networks (nodes are possibly low cost)	Costly at-sea operations and networks composed of expensive high-value assets	Algorithm validation and robustness	Algorithm validation and robustness

hostile environment and the challenging deployment and recovery processes, the operational deployment of these systems must build in a degree of redundancy. Since one must always assume that should any failures occur with the vehicle, it will most likely be lost. To guarantee the adequate persistency and to alleviate the work of support vessels, robust and convincing engineering solutions to autonomous deployment, docking and recharging need to be found [26].

Other barriers to the diffusion and deployment of underwater robotic nodes are the lack of generally accepted standards, which undermines the interoperability of systems [27]. Even if using software middleware (e.g. MOOS-IvP or ROS [28, 29]) is becoming common in the robotics community to ease the software module integration, much has to be done in payload interface and hardware standardisation. A similar problem is also present for underwater communications (see Section 5), where only recently, for the first time a physical-layer communication scheme, called JANUS [30], has been accepted as an NATO digital underwater communication standard. This is the first step towards the usage in the community of digital underwater communication standards.

1.2.2 Lack of available oxygen for combustion engine: The inability to operate a combustion engine, due to lack of available oxygen, severely limits the power and endurance of AUVs. Current solutions must rely on a battery to provide limited electric power to the propulsion mechanism – and all other on-board systems. As an example, the batteries currently employed on-board CMRE AUVs provide for around 6 kWh resulting in an endurance of 16 h at two knots. For comparison, only 1 gallon of gasoline provides around 33 kWh. With power requirements proportional to the cube of speed any increase has a significant impact on the remaining endurance. Therefore, finding a trade-off between endurance and speed generally drives the employment of AUVs towards a subset of missions in which their relatively slow speed will not impact greatly on overall performance.

If however the AUVs are requested to perform an escort mission, in which they must keep pace with some high-value unit, their lack of speed will be severely prohibitive and additional solutions, for instance diesel engine ASVs, should be pursued.

1.2.3 Severely limited sensing and communications: The underwater domain comprised of salt water is highly conductive resulting in the dissipation of electromagnetic waves and extremely rapid attenuation. For instance, the attenuation in sea water for electromagnetic waves is given by $1400f^{1/2}$ such that for just 100 m the losses at 200 MHz are 20,000 dB [31]. By contrast, the attenuation of low-frequency sound (2 kHz) over 20 km is <3 dB. The lack of electromagnetic propagation has severe consequences for both detection and communication performance – both of which are central to the utility of AUVs. In the absence of radar, underwater detection must rely on the transmission and reception of sound – *sonar*.

Detecting and tracking objects with sonar is complicated by the underwater environment (further details can be found in Section 3). High clutter is in fact usually present especially in littorals, which are characterised by poor sound propagation conditions. Changes in the sea water temperature and salinity with depth result in the bending of sound waves possibly allowing a target to remain hidden from the transmitted pulse of an active sonar. Communication must also rely on acoustics with the already mentioned consequences for both bandwidth and range (see also Section 5). These limits strongly impact both on the possibility to remotely control or monitor the activities of the robots and on information sharing among the nodes, creating problems in the network coordination and in the data fusion process.

Another major impact of the attenuation of electromagnetic waves is the lack of availability of the GNSS. As a consequence the vehicle itself may not know precisely where it is located, resulting in a location estimation error of any detected objects or mission way points. AUVs typically navigate by either inertial navigation or through a bottom DVL, or a combination of both. The latter requires that a sonar signal is bounced off the sea bottom allowing the speed and heading of the vehicle to be determined from the resulting Doppler shift. This method however limits the operation of the vehicle to a maximum sea bed depth with which the sonar signal can reliably interact. Recent solutions require that the robot interacts with a number of buoys deployed in the area of operation to self-localise [32]. Current research trends aim to use collaborative approaches to localise the nodes of the network [32] and will be described in Section 2.1.

1.3 Robotics surveillance networks

From a robotic network perspective, a general underwater surveillance mission might be divided into three phases:

- *Phase 1*: area search/patrolling.
- *Phase 2*: analysis and evaluation of target(s) cues.
- *Phase 3*: target(s) prosecution/neutralisation.

In Phase 1, the robotic nodes are driven by area coverage objectives, such as exploring or patrolling a region [33, 34], while guaranteeing a desired probability of detection. We talk of area search (or exploration) when the targets are fixed, and we talk of patrolling [35, 36] in the case of mobile targets. In both cases, targets must be detected, but patrolling needs to guarantee a desired level of coverage while respecting some defined temporal constraints dictated by the problem under investigation.

Nodes switch to Phase 2 when cues about possible targets are detected and can be scrutinised to make decisions such as to identify tentative targets, using on-board classification algorithms [3, 37–39].

When some of the cues can be associated to a target, nodes move to Phase 3, which is dedicated to target(s) cues prosecution. In this case, the robots need to make decisions and act to increase the tracking performance to classify and identify the target, and, depending on the application, to neutralise it. For instance, during this phase, in an MCM scenario, mines are identified and neutralised [40]; in ASW the AUVs might manoeuvre to increase the tracking/classification performance [41, 42].

The concept of robotics surveillance networks is sketched in Fig. 3. At the lowest level, an *executive layer* acts as the interface with the robot hardware, i.e. sensors and actuators. It collects the data from sensors and provides them to the detection, classification, localisation and tracking (DCLT) chain. The *signal processing* module is in charge of detecting echoes from targets in the presence of noise and reverberation. The output is a set of contacts (or detections), typically consisting of range and bearing measurements. Particular attention has to be paid in the selection of the appropriate algorithms due to the difficulties of the underwater scenario, characterised by low target probability of detection (PD) and high clutter levels. The produced contacts are then passed to the *tracking and data fusion* module. This has the role to spatially and temporally filter the acoustic measurements to produce target tracks. Difficulties arise in the association of contacts to the targets, since multiple targets may be present at the same time in the region of interest. Information received from other robotic nodes (e.g. contacts or tracks) can be used to improve the track creation quality and to support the target classification. The *classification* module, based on the available information and on a world model (i.e. a description of the robot working environment), has the crucial role to select among the present tracks, those who are likely related to the target(s). The output of the DCLT, together with higher level information, such as mission objectives and environmental characteristics, is passed to the *autonomy* engine. This module makes it possible for the robot to adapt to the collected measurements and to re-plan its strategies to achieve the mission goals. Note that the availability of communications is crucial at different levels of this structure, as it can be beneficial for the tracker to fuse data originating from its collaborators, as well as at the autonomy level where communications allow the robots to cooperatively select the optimal strategy and to send/receive data and commands to/from the C2 centre.

It is useful to clarify here that the concept of *autonomy*, in robotics, may have quite different meanings. In some applications, this also includes automatic operations, such as in the case of an industrial robotic arm repeating the same movements without human supervision [43]. In this paper, we think of autonomy as *the ability for a robot to choose actions or behaviours, on the basis of prior information or collected data (the experience), in order to achieve some goals.* Autonomy is the key element of a robotic network, and it is the enabler for efficiency and robustness in real-world applications. For the implementation of this concept, one important constraint lies in the ability of the selected algorithms to be executed in real-time on the computer on-board the robots, typically characterised by relatively low computational power.

While there are some examples of deployed underwater surveillance networks composed of fixed sensors and manned vehicles [4, 21], robotic surveillance networks are still an open field of research [20] and several challenges peculiar to the underwater scenario must be addressed.

This paper is organised as follows: Section 2 deals with the autonomy aspects of cooperative robotic networks, while Section 3 tackles the robotic sensing problem in environments characterised by low probability of detection and high level of clutter, i.e. the sonar problem. Multitarget tracking (MTT) approaches, which process the detection data in space and time thus producing coherent target tracks, are described in Section 4. This section also presents the opportunities provided by data fusion to increase the DCLT performance. Section 5 describes the challenges of underwater communications. This section also discusses solutions currently adopted together with recent advances and trends to increase the reliability and robustness of communications in the underwater domain. Finally, Section 6 draws the conclusions.

2 Autonomy in underwater robotics

The typical approach to set up AUV missions in operational scenarios is based on using scripted sequences of actions with generally little or no autonomous decision making [44]. According to this method, each robot has a set of pre-designed mission steps that it must follow one after another. This is attractive because it ensures a high level of predictability, and it might be especially important when the robot operates in challenging environments, as for instance in the case of deep water exploration for geoscience applications [45], where the environment itself already provides a high degree of uncertainty. In this case, the robot performs the work but the human operator still maintains most of the control. If

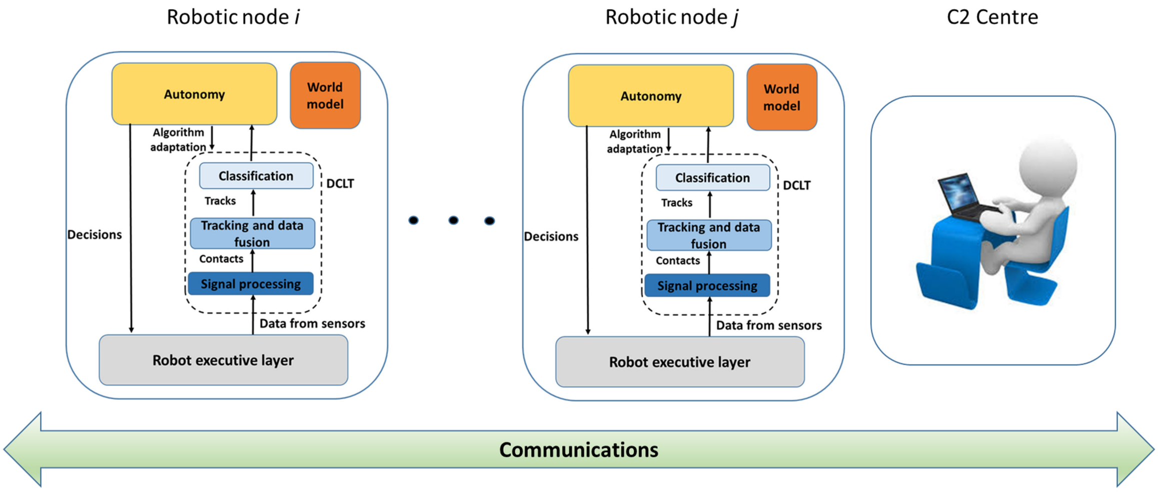


Fig. 3 *Robotic surveillance network concept. Robotic nodes receive data from sensors and through the signal processing chain (detection, localisation, tracking, and classification) produce processed information for the autonomy engine, which makes decisions for the robot. Decisions are made also based on the information acquired about the environment which is used to build a world model. Communications link all the nodes and the C2 centre enabling data fusion and cooperative decision making*

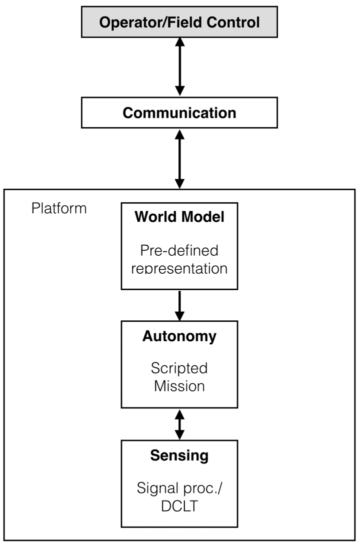


Fig. 4 *Scheme of model-driven missions. Based on an a priori world model, the mission is planned before the deployment as a scripted sequence of actions. Generally, the vehicles follow the mission with little or no autonomous decision making. After the vehicles are recovered, the collected data are scrutinised, the world model updated and a new mission is planned. This approach provides a high level of predictability, at the cost of low flexibility*

pre-designed missions are properly designed, they can guarantee uniform area coverage in a definite time. This planning approach is guided by an a priori model of the world and by the mission objectives (see Fig. 4) and can be named *model driven* [46].

Representative examples of pre-deployment mission planning are reported in [47, 48] in the case of relatively large-scale missions of up to 400 km and up to 4 days operations and in [49] for hydrothermal vent prospecting. The authors rely on multi-phase exploration methods, in which additional surveys are planned on the basis of the information collected by the AUV in previous dives during the trial. Similar multi-phase methods are also typically used in MCM applications [3], where the different phases of the mission (detection, classification, identification and mine neutralisation [50]) are performed sequentially with highly specialised robots covering pre-designed paths. In the case of robotic networks, the usage of offline planners mainly means that each robot has to be associated to a specific task (or set of steps) before the mission start, with little or even no possibility for the unit to be reallocated after the deployment. In the case of multi-vehicle systems, this usually translates into strict water-space management [51], where no more than one vehicle can be in the same area at the same time.

The mission predictability offered by model-driven robotics results in robots having little or no delegation of decision. A more general approach, pushed by the ever growing on-board computational power, is one where each robotic node of a network can be used not only as an operative component driven by external commands (i.e. model driven) but also as a reactive element able to act in response to changing conditions as measured during the exploration (*data driven*, see Fig. 5). Data-driven policies are critical in communications limited environments where the robot might need to react to the encountered events without relying on a persistent communication link with the C2 centre to make decisions. For this reason, AUV-based *data-driven* approaches are today increasingly common, with robots able to modify their paths on-line [19, 46, 52–54] as well as to make higher level decisions such as switching mission phase and optimising their planning [19, 44]. Intermediate solutions have also been proposed to find a trade-off between pre-defined paths and data-driven trajectories [55], with the AUV diverting from a pre-planned track in response to the collected data.

The increased quality in data collection provided by adaptive, data-driven robots is also beneficial to update the world model used for the decision-making process. For instance, data assimilation techniques [56, 57] can be used to improve acoustic models and predict the effects of sound propagation to gain an insight into the likely performance of a given sonar system.

Data-driven strategies can be seen as an instance of sensor management [58], by considering the sensorised robotic platforms as mobile sensors. In this case, the problem is usually formulated as a stochastic control problem [19, 58], in which the degrees of freedom of a sensor system (e.g. the paths of autonomous sensorised robots) are controlled to achieve some operational objectives. The objectives are quantified through suitable cost functions to minimise or through more general utility functions, typically composed of a reward, that should be maximised, and of a cost part [59], which must be minimised. The concept of utility is central in task allocation problems [59, 60] and will be further discussed in Section 2.2. An optimal or suboptimal policy is sought to achieve a desired configuration for the sensors on the basis of the available information from prior measurements and models of the environment, subject to the constraints of the problem under investigation.

Utility (and cost) functions can be composed of deterministic and stochastic components. The deterministic part can include, for instance, the energy cost for a given movement and sensing action or bandwidth costs during the communication process. Stochastic costs can include the predicted tracking accuracy or the predicted

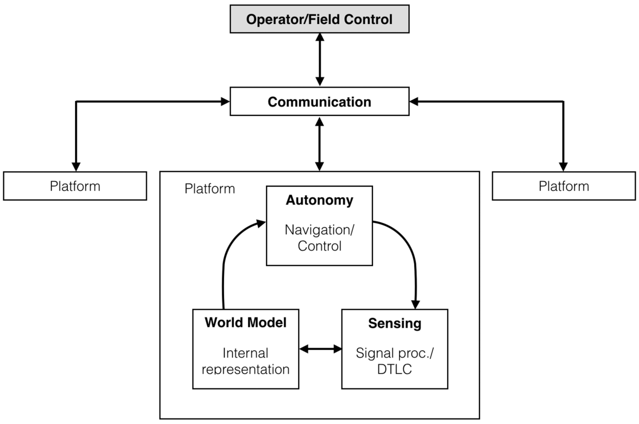


Fig. 5 *Scheme of data-driven missions. The vehicles, on the basis of the collected data, modify their path or other parameters. The collected data are used to update the a priori world model. This increases the effectiveness of the adaptive mission. More platforms are indicated, since through exchanging information they can use cooperative adaptive policies. Data-driven approaches provide flexibility and a possible increase in mission performance, but they do not assure the predictability of pre-designed missions*

entropy of a probability distribution of interest (e.g. target location) and/or the predicted gain in information [61].

There are two approaches to sensor management: *task-* or *mission-driven* and *information-driven* sensor management [58]. The former chooses sensor actions based on a given performance metric or error quantity directly related to the mission objectives. Mission-driven performance metrics for the problem of AUVs and multistatic active sonar include:

- Maximising the probability that if a target were present, it would have been detected given some a priori target probability distribution (often assumed to be uniform).
- Maximising the probability of detection or track formation over multiple platforms (for data fusion).

The robot action $\hat{\boldsymbol{u}}$ is chosen as the optimal action $\boldsymbol{u}$ in the set of all possible actions U which minimises some cost function $\epsilon(\boldsymbol{x}, \boldsymbol{u})$, where $\boldsymbol{x}$ is the state of interest, for instance the target position. In the case of stochastic modelling, the cost function can be weighted by the probability density function (PDF) conditioned on the observed data $\boldsymbol{z}$. One possibility is to minimise the expected value, that is to search for $\hat{\boldsymbol{u}}$ such that

$$\hat{\boldsymbol{u}} = \arg \min_{U} E[\epsilon(\boldsymbol{x}, \boldsymbol{u})] = \int \epsilon(\boldsymbol{x}, \boldsymbol{u}) p(\boldsymbol{x} | \boldsymbol{z}) \, \mathrm{d}\boldsymbol{x} \tag{1}$$

Alternative solutions for the stochastic component of the cost function are represented by the use of some norms of the predicted posterior covariance of a probability distribution of interest given the adopted sensor policy [56, 62, 63]. Depending on the application, several criteria can be used and lead to different sensor policies. For instance,

i. The minimisation of the trace of the posterior covariance matrix is used to reduce the overall level of uncertainty over an entire region, (A-optimality) [56], while the minimisation of each single variance entry makes it possible to obtain different monitoring objectives in different parts of the area [64] (A_η-criterion).
ii. The minimisation of the maximum diagonal value is used to prioritise locations that are most likely to contain extreme values (G-criterion) [56].
iii. The minimisation of the maximum eigenvalue can be used to minimise the variance of the worst estimated spatial pattern of variability hence avoiding the presence of a highly predominant error mode (E-criterion) [56].
iv. The minimisation of the determinant of the covariance matrix makes if possible to reduce the volume of the confidence region (D-criterion) [65].

Information theoretic costs have also been used to design the objective function [58]. Information-driven sensor management chooses sensor placements and actions that maximise a measure of the information gain, or of some function of the PDF conditioned on the observations $\boldsymbol{z}$ and the sensing actions $\boldsymbol{u}$ [66, 67].

Several functions of the fisher information matrix (FIM) [58], such as its determinant and trace, have been adopted in different applications [68]. Maximising the FIM is equivalent to the minimisation of its inverse, the Cramer–Rao lower bound (CRLB). The CRLB is the lower bound of the variance of any unbiased estimator, and its minimisation implies a reduction of the estimation uncertainty and hence a better estimate [69, 70]. For instance, in [71], the posterior CRLB was used for multisensor scheduling, whereas in [72] the Fisher information gain is used as a metric for the effectiveness of the sensor assignment in a multisensor and multitarget tracking application.

As detailed in [58, 73], using the information gain as optimisation cost function has the advantage of making the system more robust to model mismatch and changing objectives as for example when switching from detection to tracking. Its main limitation however lies in its requirement for a parametric model of the observations (often assumed Gaussian) and in giving only a local measure of information [58].

To overcome some of these limitations, other information measures such as entropy and mutual information have become more common in the research community in recent years [58, 74, 75]. The objective of the optimisation becomes the expected update in the posterior entropy. In contrast to covariance-based objective functions, entropy has the advantage of quantifying areas of probabilities and not only the average deviation of a single point. It is a measure of how much additional information is needed to infer the exact value from an estimate [76] and predicts an average distance between the approximate predicted and filtered state densities for each sensing policy. The distance can be based on the Kullback–Leibler or the Rényi divergence between the prior and posterior distributions [58].

An interesting approach is the one proposed in [77], where the authors control the sensors to minimise the expected future uncertainty of the target state using the structure of the probability distributions of the target states and of the measurements for a specific sensor configuration. Here, the mutual information between the sensors and the target state is obtained after using a particle filter to represent the posterior probability distribution. The approach is scalable to increasing network sizes and approximations of the mutual information are provided to handle the complexity. Moreover, the usage of a particle filter makes the method non-parametric and able to directly use non-linear and non-Gaussian target state and sensor models. The efficiency of the policies, a key aspect of entropy or mutual information methods, is also tackled in [78] where the sensor control law maximises the Cauchy–Schwarz quadratic mutual information between occupancy belief distributions and future measurements that can be made by mobile sensors.

Use of information theoretic costs to manage sensor devices (i.e. autonomous vehicles) has been applied to different models and sensor management scenarios. Examples can be found in [79–82] where a new probabilistic roadmap method is presented that mixes the robot path planning with the capability for the robot to gather target information using its on-board sensors.

As an alternative to probabilistic formulations, Bullo *et al.* [83] describe a number of geometric approaches tackling the area coverage and the deployment problem. The geometric approach has the advantage of making it easier to theoretically analyse the system performance, especially because it is often based on a bounded uncertainty assumption.

Independently of the cost function, one key issue is the planning horizon considered in the optimisation [84, 85]. The sensing actions can in fact move better towards the overall objective when the evolution of the tactical scene in the future is considered. Some

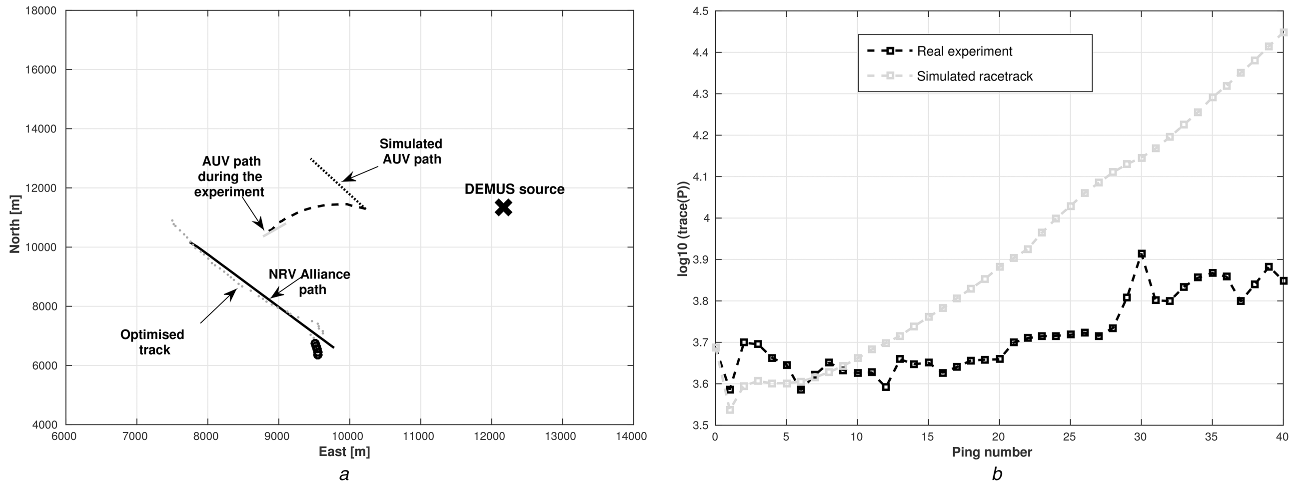


Fig. 6 *Example of a data-driven algorithm used in an underwater surveillance application [42]. Data from Co-Operative LittoraL Asw Behaviour in 2013 (COLLAB13) sea trial, 5/7/2013 – Groucho AUV, the target was an the echo-repeater artificial target towed by the NRV Alliance*
(a) The real path followed by the AUV controlled by the non-myopic algorithm is visible in black. In grey, the array heading is shown. In dashed black, we also report the AUV trajectory continuing the trackline it was following at the moment of the activation of the data-driven algorithm, for a performance comparison with the data-driven strategy. In grey, the NRV Alliance path is visible with the prosecuted track produced by the on-board tracker is drawn in dotted black. Black circles are the prediction of the algorithm for the target position, ***(b)*** computed $\log_{10}(\mathrm{tr}(\boldsymbol{P}))$, the trace of the posterior covariance matrix of the target location error estimate of a tracking filter, in the case of the AUV controlled by the non-myopic algorithm and of the simulated rectilinear path. At the beginning of the manoeuvre, the measurement localisation error increases with respect to the fixed path due to the array bending. Then, the manoeuvre leads to an important error reduction in the estimate of the target position if compared with the rectilinear path

actions that do not lead to a decrease in the cost function at the next step of prediction can be beneficial when a longer future horizon is taken into consideration. Methods that take into account multiple steps into the future are called non-myopic, in contrast with the approaches that try to optimise the cost function by looking only at one prediction step that are called myopic or greedy. Non-myopic policies have been tackled with different theoretical frameworks, such as Markov decision processes (MDP) or partially observed Markov decision processes (POMDP) [86]. The resulting problem can be theoretically solved optimally using dynamic programming techniques [84]. With the increase of the planning time horizon, the problem becomes prohibitive from a computation standpoint (a large action and/or actions space may make the problem prohibitive from a computation point of view as well [87]), and even more so when the algorithms need to be implemented on resource-limited robots. Approximate solutions such as rollout or model predictive control [87], even if suboptimal, are used to find a trade-off between results and required processing resources. Myopic sensor management strategies are less complex alternatives to multi-stage policies which offer computational simplicity at the expense of a possible increase of performance provided by non-myopic algorithms [58]. One example of these approaches demonstrated at sea for an ASW surveillance network application is reported in [41]. In this work, an AUV minimises the one-step predicted localisation error of a target with the aim to improve the tracking performance of a multiple hypothesis tracking (MHT) filter. Even if there are many practical cases in which myopic approaches give acceptable performance, non-myopic policies have been demonstrated as effective in underwater surveillance scenarios. In [88], the AUVs optimise the predicted probability of detection of the target computed as a function of the hypothesised target position, receiver trajectory and range-dependent environmental parameters. In [89], the AUV trajectory is controlled to optimise the expected SNR looking at the future evolution of the tactical scene. In [42, 90], a receding horizon strategy has been proposed to control the heading of an AUV with the objective to seek for the control sequence which minimises the sum of the trace of the posterior covariance matrices of a tracker over a planning horizon. The approach relies on an on-line acoustic model [91] and has been demonstrated during several ASW at-sea trials to increase the real-time tracking performance. Results are reported in Fig. 6, where a simulated trackline trajectory is also analysed to evaluate the benefits brought by the data-driven policy. In [92], a target tracking application is proposed, where the coupling between a non-myopic control law with a particle filter and a three-dimensional representation of the underwater environment allows the AUVs to move along the water column to reduce the uncertainty in the localisation of the target depth.

2.1 Autonomy and underwater communications

Even when data-driven approaches are used, the typical assumption for a robotic network is still that continuous information exchange between the robots and between the robots and the human operator can be available [20, 93]. When this is not possible, the robot decision making becomes a key point to accomplish the mission objectives. The spectrum of autonomy architectures ranges from purely reactive policies to deliberative solutions. In *reactive* or *behavioural* architectures [94, 95], the mission is described as a sequence of pre-defined 'behaviours'. The 'behaviours' are based on the sense-react principle and are activated on the basis of the external stimuli and mission objectives. In purely reactive architectures, a world model is not used since the action is driven by the collected data [43, 96]. Reactive approaches provide simple solutions effective also in highly dynamic environments with in general limited computational requirements. Alternatively, *deliberation* includes projecting plans which balance near-term objectives with end-term or time changing goals [44]. Deliberation architectures rely on a world model, which is used to incorporate the acquired information with a priori knowledge of the scenario. This model is the basis to make plans at the cost of an increase in computational load and some possible delay in the robot's actuation. For these reasons, typical solutions used in real-world applications consist of *hybrid* architectures in which a deliberative layer works in synergy with a lower-level reactive component dealing with phenomena in which a fast response is required (e.g. obstacle avoidance etc.) [97–100].

One important example of a hybrid architecture is represented by the nested autonomy concept, developed at MIT [28] for distributed undersea surveillance. The nested autonomy control paradigm is an approach to combine a system of unmanned platforms for large-scale autonomous sensing applications. It assumes heterogeneous platforms with different communication bandwidth, connectivity, and latency and uses both platform-to-platform collaboration (e.g. sensor fusion) and platform-to-operator communication to overcome the limitations provided by each individual sensor node [101]. The concept builds on top of open-source behaviour-based [94, 95], autonomous C2 architectures (e.g. MOOS-IvP [28]), and makes it possible for each platform to autonomously detect, classify, localise, and track an episodic event in the ocean, without depending on any operator C2. The prosecution of the event, such as the detection and tracking of a target or of a feature of interest, may be initiated by the operators [28] if communication is available, or be entirely autonomous and decided by an on-board detection capability. In [39], the on-board decision-making engine of the AUVs is able to autonomously switch between different pre-defined behaviours associated with different mission states (exploration and prosecution), with the final objective of finding a trade-off between area surveillance and target cues prosecution.

In the general nested autonomy concept, the event information collected by each robotic node in the network is reported back to the operators by transmitting an event report, periodically or asynchronously. Within this concept, collaborative processing and cooperative control can and should be exploited but only as allowed by the communication channel (see, for instance [28] for collaborative tracking of coastal fronts and man-made sources and [88] for cooperative area search). It is important to highlight that the nested autonomy concept does not eliminate the operator from the decision process. Thus, whenever a communication opportunity arises, the operational paradigm will take advantage of any information that can be received from the operator or collaborators in the network. More than this, the operators are still responsible to deploy the number of units available in a way which is optimal for the current situation so that there is the highest probability for capturing the episodic event of interest. The intermittency of the underwater acoustic communication channel makes it imperative that each node is capable of completing the mission objectives in the total absence of communication connectivity.

2.1.1 Underwater navigation: One additional challenge related to the communication difficulties of underwater systems lies in the ability for the robots to navigate when underwater. The rapid attenuation of GNSS and radio frequency signals coupled with the low bandwidth and unreliability of typical underwater communications and the unstructured nature of the undersea environment implies that there is no access to a global positioning system. Notwithstanding these challenges, AUV navigation and localisation are today experiencing continuous advances.

Typical solutions to solve the AUV localisation problem [102] are based on employing expensive inertial sensors commonly in combination with fibre optic gyros (FOG) to measure the vehicle orientation, and with pressure sensors and bottom DVLs to measure the vehicle depth and speed, respectively, with a necessary trade-off between performance and costs [32]. Alternative solutions rely on deploying dedicated beacons in the region of interest [32] (e.g. long-base line (LBL) or ultra-short base line), or requiring periodic surfacing of the AUV. These solutions are today being replaced by dynamic multi-agent systems and networks that allow for rapid deployment and a higher degree of flexibility. A group of vehicles, endowed with communication capabilities, can use cooperative localisation approaches to support their navigation. In general, cooperative localisation relies on range/bearing measurements that a vehicle can obtain periodically from the other network nodes through acoustic communication. These measurements are used to improve the node's self-localisation. This kind of approach can bring several benefits. Robots take advantage of navigational services provided by the network with no need of a deployed infrastructure (e.g. traditional LBL with moored beacons). These approaches open the possibility to use fleets of heterogeneous vehicles, in which a more capable vehicle (equipped with expensive FOGs and DVLs) supports the navigation of cheaper, less sensorised assets [32]. In [23, 103], the integration of navigational services into the communication stack of an *ad hoc* underwater acoustic network enabled the improvement of the navigation and localisation capability of a fleet of AUVs. Experimental results reported in [104] show the ability of the network to limit the navigation errors both in short-range applications (tens of metres), characterised by a short refresh rate, and with vehicles navigating at long range (tens of kilometres) with the nodes joining an already existing surveillance network. Moreover, the presence of a robotic network makes it possible to rely on nodes that can make decisions and move to optimise their position when a change in the communication/localisation performance is detected. Discussion on the optimal geometric configurations of mobile surface sensor networks is described in [105, 106]. The FIM, or the CRLB, corresponding to a 3D scenario is used to characterise the sensor configuration that yields the best precision with which the position of a target can be estimated. The determinant of the FIM is used as an indicator of the performance that is achievable with a given sensor configuration, and hence its maximisation leads to the most appropriate sensor formation geometry. Note that the geometry of the optimal sensor configuration depends strongly on constraints such as the type of available localisation devices, the maximum number of sensors and/or on the limits on sensor placement, as well as on characteristics of the acoustic channel, and that different formulations are therefore devised based on the available measurements (range only versus bearing only). An experimental demonstration of these approaches has been reported in [70] where a constellation of surface nodes adapts its geometrical distribution to improve the localisation performance of an AUV performing an underwater mission.

2.2 Cooperative robotics

When multiple cooperative units are deployed together, communications becomes even more important since the robots spatial locations and mutual separation have a direct influence on their communication capabilities. Recently, studies have been carried out to include communication constraints into the development of cooperative strategies for sets of vehicles [46, 107]. However, the impact of limited and/or unreliable communications has not been fully characterised. Most of the cooperation strategies proposed in the literature have been focused on cooperation of aerial or terrestrial vehicles, but these algorithms are not directly applicable in the underwater case due to the strong variation in space and time of the communication medium. Acoustic propagation, the main means of underwater communications, is strongly dependent on local environmental conditions. This implies that during the evolution of the mission each vehicle can experience abrupt changes in the channel, with a consequent variation in communication performance. Sudden reduction of the channel capacity and bandwidth, or even a temporary loss of connectivity with the rest of the team, is a frequent condition for underwater communications. In operative scenarios, not only is it necessary to share information but the ability to securely communicate becomes a key issue so that the correct data are transmitted and received by the right robots, and only among the desired group. These strict requirements open new challenges from the communications perspective (see Section 5).

The field of oceanography has developed many concepts of multi-agent robotic systems to achieve synoptic monitoring of large areas with the final objective of overcoming the limits of ship-based missions [108–110]. In this case, real-time constraints are not as tight as in the case of surveillance networks, and multi-agent cooperation can be obtained relying on radio frequency (RF)-communication when the vehicles, typically gliders, are on the surface. Representative examples of this kind of approach are reported in [111], where a full-scale adaptive ocean sampling network featuring a fleet of gliders was deployed during the 2006 adaptive sampling and prediction (ASAP) field experiment in Monterey Bay, California. The gliders were able to collectively coordinate their motion to efficiently sample the ocean, adapting their motion pattern to the spatial and temporal scales in the sampled fields, with the final objective of reducing the statistical uncertainty in the field estimates. Further details on the glider control algorithms used during the ASAP experiment can be found in [112, 113]. Using teams of AUVs for the exploration of partially known or unknown environments is also discussed in [114]. Here, adaptive cooperative behaviour is achieved by each vehicle in terms of locally evaluating the smoothness of the sampled field, and selecting the next sampling point in order to achieve the desired accuracy.

More recent examples on the use of gliders for oceanographic missions can be found in [57]. In this case, several approaches are reported including the usage of adaptive sampling via error subspace statistical estimation (ESSE), mixed integer linear programming (MILP), non-linear optimal-sampling path planning using genetic algorithms or dynamic programming and on-board routing for optimal-sampling path planning. Note that, when multiple underwater robots are available, the typical approach is still mainly centralised, which means that gliders or AUVs communicate, possibly when on surface, their known location and measurements to a unique C2 centre which fuses all this information together and sends back new waypoints or tracklines [64, 115].

To overcome the limitations of communications, distributed policies are necessary to design credible solutions in real-world surveillance applications. One of the first examples has been proposed in [6]. In this case, AUVs represented the mobile nodes of an underwater acoustic network and acted as surveillance assets. Although the vehicles could be acoustically controlled by the C2 centre to respond against intrusions, they also had the on-board intelligence to autonomously react to a sudden loss of communication [5]. A behavioural approach was used to minimise the computational and communication needs of the vehicles, which responded to simple local rules based on the available information to perform the mission and maintain the communication link with the network.

A multi-agent harbour protection application has been proposed in [36]. In this work, a team of vehicles is required to dynamically patrol a certain region applying decentralised control, using only nearest-neighbours information. The proposed solution is based on Voronoi tessellations and Gaussian processes, and it allows robustness with respect to asynchronous events such as temporary communication or vehicle losses.

An approach to the multi-vehicle coordination and cooperation of AUVs is presented in [116] based on the formalism of potential game theory. Within this setting, each robot is associated to a utility function that depends on its objective (e.g. reach a desired point, perform a sidescan survey etc.), its current action/state and the actions/states of the other robots. Each vehicle then selects its next action to locally optimise its utility function. The paper shows how very simple games can be used to steer an AUV formation in the position which best compromises between target destination of each vehicle and preservation of communication capabilities among the vehicles.

While the previous solutions exploit the presence of multiple units, every robot is considered to be equipped with the same sensing ability and it is assigned to the same and unique task of the mission that has to be accomplished cooperatively. However, when heterogeneous assets are present, more solutions become possible, as for instance, the selection of vehicle-specific tasks that depend on the ability of each unit.

To treat task allocation, that is the problem to associate tasks to network nodes, in an optimisation context, it becomes critical to decide what needs to be optimised. While the goal, at least in a cooperative setting, can simply be seen as the optimisation of the overall system performance (a robot might sacrifice its own short-term benefit for the wellness of the team), this is in general a difficult quantity to measure. To overcome some of these difficulties, the usual approach is to utilise some kind of performance estimate, which is usually defined as the *utility* of a specific task allocation choice. Each robot utility can be seen as a generalisation of different quantities used in literature to characterise a task: reward characterising the gain of accomplishing a task [117], cost it takes for a robot to execute a task [118], fitness [119] quantifying how well a robot can perform a certain job, and priority to quantify the urgency to accomplish a task [120].

A combination of these quantities is used to express the value of a task, or better, its utility. For instance, a common definition of utility is as follows [121]:

$$\text{utility} = \text{reward} - \text{cost} \tag{2}$$

Utility is a flexible measure of value that can include many different arbitrary computations. The only requirement is that a single scalar has to be produced which is used to order the candidates to a certain task. All the important aspects of the state of the robots and their environment of interest for the group performance must be included in the utility computation. Each robot must be able to compute its own utility for a certain task, and the overall group performance/utility has to be influenced by the utilities computed by each robot. It is important to note that, regardless of the method used for the calculation of the utility value, the robot's estimate will be affected by noise, uncertainty, environmental change and communication limitations.

In a general scenario, the network can allocate the different tasks of the surveillance mission to its nodes depending on the tactical situation and based on the specific environmental conditions. This problem, known as multirobot task allocation (MRTA), consists in finding an agreement between the robots of the team that have to decide how to assign a certain task to one or to some subset of the nodes to achieve the overall missions goals in an efficient manner. Specific reviews on the topic can be found in [60, 121, 122].

If we assume a linear group utility function to be maximised by the allocation, we can define the simplest case of MRTA as follows:

$$\begin{aligned}
&\text{maximise} \\
&\qquad \sum_{i=1}^{n}\sum_{j=1}^{m} \gamma_{ij} u_{ij} w_j \\
&\text{subject to} \\
&\sum_{j}^{n} \gamma_{ij} = 1, \quad 1 \le i \le m \\
&\sum_{i}^{m} \gamma_{ij} = 1, \quad 1 \le j \le n
\end{aligned} \tag{3}$$

with u_{ij} being the utility of task j when robot i is assigned to it, w_j a weighting factor and γ_{ij} an assignment variable, which may be either 0 or 1, 1 meaning that robot i is assigned to task j. The constraints means that each task can be assigned to exactly one robot and that one robot cannot be assigned to more than one task. In this case, the MRTA becomes an instance of the optimal assignment problem (OAP) [122], which can be solved in a centralised way by using the Hungarian method [122] or in a distributed fashion by using the auction algorithm [123]. In general, however, MRTA is not a one-time assignment and becomes a dynamic decision problem, since utilities may vary or tasks terminated or be created. The static assignment can no longer be considered applicable and iterative procedures must instead be sought [124, 125]. Furthermore, changing the relations between utilities, the type of the group utility function and relaxing the constraints in (3), the MRTA becomes more complex leading also to NP-hard problems [60].

Among the solutions available in the literature and of interest to our scenario, Parker [126] proposed a multi-robot software architecture tailored to the cooperative control of heterogeneous mobile robots performing missions composed of loosely coupled sub-task, as for instance when there is an order dependence. This can be considered one of the earliest demonstration of iterated assignments for multi-robot-task allocation [122]. The proposed solution, an example of behavioural approaches, is fully decentralised, with objective functions based on robot motivations (e.g. impatience, acquiescence etc.) to complete the mission. This behaviour-based architecture allocates tasks by maintaining, for each team member, levels of impatience and acquiescence concerning the available tasks. A robot gets impatient if it realises there is a task that nobody is executing. Acquiescence is the mechanism that makes a robot relinquish a task if it estimates its performance is below expectancies. These motivations are combined to form, in effect, a utility estimate for each robot-task pair. Robots broadcast periodically their current commitments influencing the nearby team mates actions. L-ALLIANCE, an extension to the original work, learns its assignment algorithm from experience, and the resulting algorithm is similar to a greedy algorithm which repeatedly takes the best valid option. However, when well trained, L-ALLIANCE assignment is superior to a greedy assignment although it is not guaranteed to be optimal.

A similar idea is developed in [127, 128] called threshold-based task allocation. Each robot has an activation threshold for each task to be performed. The robots define the stimulus as a value that reflects the urgency or importance of performing a task. The stimuli are perceived continuously for each of the tasks. When the value exceeds a certain threshold for a robot that robot executes the task. When the stimulus becomes lower than the threshold, the robot interrupts the behaviours which are executing the task. This reaction to the stimulus can be deterministic or probabilistic.

Probabilistic frameworks, such as MDP or POMDP as those presented in [121], can be used to provide an optimal control strategy in tightly coupled domains. However, the main limitation to their use is that they quickly become intractable even for small problems. Approximation techniques need to be further investigated for an effective use of these frameworks in real scenarios [129].

One other family of task allocation algorithms is represented by *auction/market-based* approaches. These methods, which are distributed in nature, have the possibility to adapt to changing conditions, while mimicking some of the aspects of more centralised approaches, without significantly reducing the fault tolerance/scalability aspects. The underlying philosophy of market-based methods is that of distributing common resources among the team members taking inspiration from human market economies where individual pursuit of profit leads to the redistribution of resources and to an efficient production of output [130]. In this virtual economy, tasks are traded as commodities and virtual money acts as currency, while robots compete to be assigned to a task by participating in auctions. When the system is correctly designed (i.e. costs, revenues and auctions mechanisms), each robot acts to maximise its own profit while moving towards an increase in the group efficiency. Most of the research on multi-robot-task allocation has been confined so far to terrestrial robotics and usually tested in simulation [131–133], hence without the required attention to the communications perspective. Further research is therefore needed to adapt and generalise the work presented in the literature to design credible solutions in real-world underwater scenarios. Communications failures must be explicitly taken into consideration, by investigating and testing redundant task allocation schemes to guarantee the sufficient required robustness [134]. The next section goes into the details of the underwater robotic sensing problem, i.e. the sonar problem.

3 Acoustic signal processing

In underwater surveillance applications, sonar systems are generally used for target detection and localisation, with the detection usually achieved at the same time as localisation [135]. The process of localisation involves bearing and range estimation [136]. These objectives can be accomplished actively or passively, depending on the scenario and specific application. An overview of signal processing approaches for automatic target detection and localisation is provided. The objective of these approaches (see the signal processing module in Fig. 3) is to produce the contacts (also called detections), which are target measurements in range and bearing. The presented methods may be implemented on unmanned autonomous vehicles running in real time on a network of robots (see Fig. 3). The detections are typically numerous and not readily associated with targets (if any are present). The detections must be spatially and temporally associated in order to produce target tracks, as detailed in Section 4. Significant example of the wide open literature available on classification of objects on the seabed from high-frequency active sonar imaging is [137–141]. Also passive acoustic classification of noise sources such as marine mammals or surface vessels is widely described (see, for example [142–144] and cited references). Open literature is instead limited on classification of underwater mobile objects through active low-frequency sonar; some significant works are reported in [37, 145, 146]. A detailed review on classification is not part of this paper.

In many active sonar systems, a pulsed signal is transmitted to the target and the scattered echo is sensed by a receiver. The transmitter and receiver may, or may not, be colocated. Directional receivers, in the form of hydrophone arrays or vector sensor arrays, are required to estimate the target bearing, typically through beamforming algorithms [147]; the range of the target is determined from the time delay of the echo. A gain in detection performance can be obtained through the increase of spatial directivity afforded by towing a linear array of hydrophones, essentially filtering out unwanted noise in directions beyond the look direction. However, the addition of a long array of hydrophones places additional load on the AUV propulsion system and subsequent endurance.

In passive sonar, the target is detected from acoustic signals emitted by the target, which is localised by exploiting the time coherence of the emitted signal received at spatially separated points.

In both approaches performance limitations arise as a result of:

- Sound propagation loss through the water channel, which mainly depend on the sound speed profile along the water column, but also on the signal frequency as well as the characteristics of sea bottom and sea surface, especially in shallow waters [148–151].
- Additive ambient noise at the receiver [152], given a device which is able to measure the minimum sea ambient noise in the bandwidth of interest.
- Other effects of the environment [153], such as a wide variety of channel dispersions in time, frequency, and angle [154, 155].

For active sonar at short range a strongly limiting factor to detection is the reverberation level, either diffused or coming from compact clutter on the seabed [156, 157]; at long range the performance is limited by ambient noise [158]. For passive sonar, a further limiting factor is the generally imprecise knowledge of the characteristics of the target emissions (either from a vessel or from a marine animal).

Cognitive sonar architecture is a concept inherited from the radar community [159]. It has been recently proposed [160–163] with the main localisation performance [164].

Among the array processing techniques of target detection, a big category is based on adaptive processing approaches [165], which includes in particular the so-called space–time adaptive processing (STAP) [166], which is a signal processing approach most commonly used in radar systems. Radar and sonar signal processing benefits from STAP in those cases where interference, either in terms of noise or reverberation [167], is present. Through careful application of STAP, it is possible to achieve significant improvements in target detection performance [168–171]. STAP involves filtering techniques based on the knowledge of the interference statistics. This can be either known a priori, or estimated from the collected data themselves along a mission. By applying the statistics of the interference environment, an adaptive STAP weight vector is formed and is applied in the beamforming approach along time.

Both conventional and adaptive approaches include beamforming of arrays that are not purely linear but maybe twin, triplet, or volumetric, which are selected in order to overcome the strong limitation of port-starboard ambiguity typical of linear arrays.

3.1 Active sonar signal processing

A generic signal processing chain in active sonar is sketched in Fig. 7. It includes signal conditioning, possible sub-band splitting, beamforming, matched filter (in the case of broadband waveform), normalisation, clustering, and finally contact detection (examples can be found in [147, 172, 173]).

The selection of specific signal processing approaches strictly depends on the sonar configuration. One of the possible classifications of sonar systems is between *monostatic* and *multistatic* systems [174], and refers to the geometry of the sonar configuration. In a monostatic system, the source and receiver are

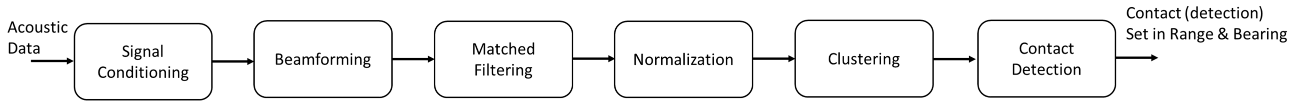


Fig. 7 *Generic signal processing chain up to the contact formation (range and bearing) in active sonar. Data from a hydrophone array are acquired and conditioned. The time series on each of the array's hydrophones is mathematically transformed in such a way as to produce a time series per look direction (beam) via beamforming algorithms. For each beam, the time series is filtered using a replica of the source's outgoing pulse (matched filter), resulting in a pulse-compressed time series allowing computation of the measurement ranges. The matched filter output is normalised to reduce diffuse reverberation level and calculate the SNR per point. After the clustering of the measurements, an SNR threshold is applied to the normalised data to form contacts (also called detections) [147]*

colocated (on the same platform). The typical, traditional ship-towed sonar belongs to this category and implies less geometrical uncertainties and conceptually simpler processing approaches [170]. A multistatic system distributes one (or more than one) source and multiple receivers in a certain area. This is the natural configuration of a sonar system based on a heterogeneous network of robots, and has several advantages, such as the possibility of exploiting spatial diversity and higher flexibility [175, 176], which may lead to the capability to overcome the problem of dead zones, greater coverage, and high potential for data fusion at contact and/or track level (see Section 4). Spatial diversity is particularly attractive in active sonar as the scattering response of an extended target is always highly aspect dependent [177, 178]. The most favourable geometric condition in order to have the highest SNR is catching the specular reflection, or 'glint', of the insonifying signal on the target [179]. However, multistatic geometries lead to increased signal processing challenges, especially if all the assets, either transmitters or receivers, are in motion. Data contain the direct blast along with the target echo, which is useful in order to understand range and bearing of the source at each time, but needs to be identified through dedicated processing [180]. The estimation of target speed from a Doppler frequency shift is more complicated, especially if the target is manoeuvring [181].

3.1.1 Waveform design and selection: There are two main categories of waveforms used in sonar: the frequency modulated (FM), broadband waveforms, and the constant frequency, narrowband waveforms, also called continuous waves (CW). The FM waveforms can provide good target range information, while the latter ones allow good Doppler-shifted frequency measurement and may be more effective under high-reverberation conditions, but do not allow a good range resolution. One of the major research topics of the latest decades in the field of active sonar is related to the exploitation of advanced waveforms and optimisation of waveform selection [182] in order to respond to specific needs, such as optimisation of performance under either reverberation-limited conditions [167, 183], noise-limited conditions [158], target tracking optimisation [184], geometrical conditions that emphasise Doppler effect [183] trying to keep good range resolution [185–187]. This is in perfect agreement with the concept of cognitive sonar, as the waveform type or parameters can be adaptively changed on the basis of the current environmental characterisation [182].

3.1.2 CAS versus PAS modes: Two main active sonar modes are currently used, in particular for ASW applications: the more traditional pulsed active sonar (PAS) and the continuous active sonar (CAS). Conventional PAS has duty cycles in the order of 1% which means that for the most part of the ping interval the track is out of date. In contrast, high-duty-cycle (up to continuous) active sonars have up to 100% duty cycle which enables continuous updates to the track, hence limiting the data association error inherent to a PAS system. When the duty cycle is high but <100%, we talk about high-duty-cycle active sonar (HDCAS) mode. Theoretically, increasing the processing interval increases target detectability, but in practice other factors should be considered. In real acoustic environments, sound propagation is subject to temporal and spectral spreading effects, and these may limit the processing gains to lower levels than expected. Target Doppler can also become a more significant issue with longer processing intervals.

Traditional PAS waveforms, such as linear frequency modulated (LFM) broadband pulses, have been adapted to CAS. One may want to maintain the same bandwidth for a CAS system as for the PAS system it might replace. This will provide a significant increase in the time-bandwidth product but may not produce the increase in gain anticipated if there are significant coherence limitations associated with the acoustic channel [188–191]. If sub-band processing is applied, it can not only provide a higher measurement rate [147, 192] but can significantly mitigate the effects of limited time coherence of the channel [191] in CAS mode. However, matched filter gain may decay due to the more limited bandwidth used in each time interval. To experimentally examine the advantages and limitations of CAS (or HDCAS) with respect to the more traditional PAS mode [193], a series of sea trials have been conducted. Among others, the 2013 sea campaign *Target and Reverberation Experiment (TREX-2013)* conducted in the Atlantic was partly devoted to evaluate the impact of pulse duration on echo statistics [194] and evaluate sonar performance with respect to environmental spreading effects, the target's physical extent and Doppler effects [190, 195]; the *Littoral Continuous Active Sonar (LCAS)* joint research and multinational project started in 2015 and, led by NATO STO CMRE, aims at the evaluation of CAS performance in littoral waters, generally characterised as a high-reverberation environment, hence more challenging for CAS. Two sea campaigns were conducted in 2015 and 2016, respectively, in Mediterranean coastal waters in the context of LCAS project [191].

A recent, alternative to CAS and PAS is a multiple-input multiple-output multiple-input multiple-output (MIMO) approach proposed in [196]: a modified code division multiple access (CDMA) waveform is adapted to sonar constraints. This offers a mid-way solution between PAS and CAS allowing the user to decrease the PRI and then increasing the hits on target but not at the cost of sacrificing the full bandwidth exploitation.

3.2 Passive sonar signal processing

Passive sonar aims to detect and localise noise sources that may be biological (such as cetaceans, shrimps, and invertebrates), natural (such as seismic waves) or man made (such as surface or underwater vessels, wind farm activities etc.) [154]. Noise sources may be intermittent (i.e. cetaceans clicks and whistles, sonar pings), transients (seismic waves), or continuous (vessels) [152]. The characteristics of the measurement systems (sensor array geometry, sampling frequency and bandwidth, recording strategies etc.), as well as the signal processing approaches, strongly depend on the characteristics of the noise emissions. Traditional passive acoustic monitoring networks of sensors are static (generally deployed on the bottom) and cabled [13, 197]. Some passive measurement systems are hosted on moored buoys, so that they can send data (but also results and alarms achieved through local data processing) to a shore C2 station [198, 199]. More recently, due to the spread of long-endurance, silent, small, relatively low-cost autonomous platforms, passive sonar systems hosted on networks of mobile unmanned vehicles have been proposed [144, 200–202], often based on vehicles such as underwater gliders and WaveGliders. One common requirement imposed by passive acoustic monitoring is persistence, which in general means low-power systems; this may imply strong limitations on the measurement hardware design (number of array channels, computational power), hence on the system capabilities. Another main limitation in the use of small mobile robots for passive

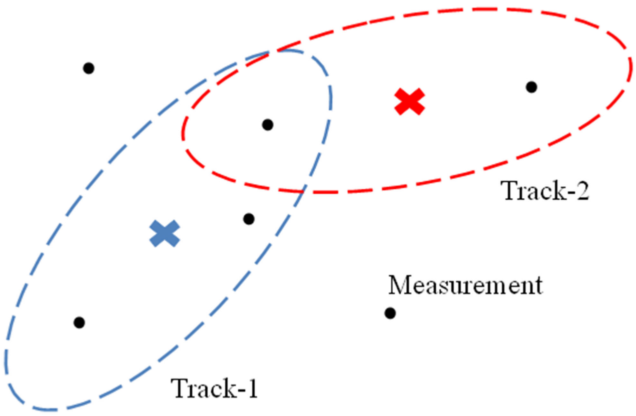


Fig. 8 *Example of the MOU problem. Two 'tracks' (blue and red) are currently active. Tracks are targets that are hypothesised to exist by the tracking algorithm. Their spatial uncertainty is represented by ellipses known as gating regions. New target-originated measurements are expected to lie within the gating region of the corresponding track. At the current time step several measurements have been collected. In general, all of them can be associated to both tracks but only the ones that are inside a gating region are likely to have originated from the target related to that region. Three measurements can be associated with Track 1 and two measurements with Track 2, one of them is in common. Each of them could be target originated or false alarms. For a reduced computational complexity, many MTT approaches consider for a given track only the measurements inside its gating regions*

surveillance is on the maximum physical aperture of the sensor array, if the targets are very low-frequency noise sources.

In some systems, the array is compact and volumetric and consists of few elements in order to meet better the constraints imposed by the size and power of its platform. In the case of volumetric array, 3D direction of arrival techniques are implemented [201–203].

The selection of the most suitable signal processing approach is conditioned by the computational load in order to achieve quasi-real-time responses [202]. Two main signal processing methodologies are generally applied for the passive acoustic detection and localisation of noise sources. One is shared with active sonar signal processing and is based on beamforming, either conventional or adaptive [136, 171] and can be computationally heavy if the array has a large number of sensors. A second interesting methodology is based on the measurement of the difference of time of arrival (TDOA) between pairs of non-colocated sensors, which is accurately related to the direction of arrival of sound (through simple trigonometric formula), if the observer is in the far field of the noise source (plane wave assumption), the time coherence is preserved in the propagation channel that separates the two sensors, and the sensors' spacing is much bigger than the signal wavelength [197]. The estimation of the time difference is generally achieved through cross-correlation of signals appropriately gated in time windows, either computed in time or in frequency [204] and thus generally fast, enabling real-time processing over a relatively high number of sensor pairs [144]. The selection of the window duration is crucial to be able to detect transients or continuous sounds and depends also on the sensor spacing and the time coherence of the channel. The approach can be easily extended to a distributed sensor array, under the hypothesis of time coherence of the signal and real-time availability of each sensor data and position in a central processing node. A set of time differences are then fused to achieve the estimate of direction of arrival (on a cone for linear arrays, on a slant plane for planar arrays, on azimuth and elevation for volumetric arrays) though a number of methods, such as a simple triangulation [197], the hyperbola method [205] or the least squared method (LSM) [206] if the number of pairs is higher than the problem dimension. While this approach provides high resolution, data association between pairs is difficult, hence is particularly suitable in presence of one target, or should be aided by an appropriate tracker in the case of multiple targets [207].

In passive sonar, target range cannot be derived from the exploitation of the time of arrival, as happens in active sonar systems consisting of synchronised transmitter and receivers. Open literature proposes a variety of approaches to achieve target localisation from pure bearing-only measurements [208]. These approaches work under the hypothesis of (at least piece-wise) constant speed and straight path trajectories of the target or use knowledge on the bathymetry.

The described algorithms allow the robots to produce contacts (or detections) in range and bearing (see Fig. 3). The contacts are typically many and not easily associated to targets (if any targets are present). The problem of associating contacts in both spatial and temporal domains to produce coherent target tracks is detailed in the next section.

4 Multitarget tracking and distributed information fusion

The MTT problem refers to the problem of jointly estimating the number of targets and their states using measurements from one or multiple sensors [209]. Problems of this kind arise in a number of scenarios and have considerable practical importance in applications such as ballistic missile defence [210], visual surveillance [211], biomedical analytics [212, 213], robotics [86, 214], indoor localisation [215, 216], and autonomous driving [217–219]. One of the first applications of MTT however was underwater surveillance from sonar measurements [220].

The MTT problem has a tradition of over 40 years of studies [221]. Its fundamental aspect is the measurement origin uncertainty (MOU), first described in [222]. MOU occurs in surveillance systems when the sensor produces clutter, i.e. false-alarm measurements, or when several targets are close to each other and it is not possible to associate measurements to targets with certainty. A pictorial explanation of the MOU is provided in Fig. 8. Measurements collected by an active or passive sonar systems are always subject to MOU. In particular, in the littoral environment a significant amount of false alarms is typically produced due to features of the seafloor or reverberation.

A trivial approach to address the problem of MOU is to perform a nearest neighbour association of measurements to targets. It has been shown that the resulting nearest neighbour filter can lead to very poor results in an environment where false-alarm measurements occur frequently [223]. One of the first promising approaches for tracking a single target in the presence of MOU was the probabilistic data association (PDA) filter proposed in [220, 223, 224]. Its generalisation to multiple targets, the JPDA filter was presented in [220]. In parallel to the PDA, a powerful alternative called the MHT was developed. The basic idea of propagating multiple hypotheses for tracking a single target was given in [225], while Reid [226] first developed a complete algorithmic approach for tracking multiple targets. A review of the JPDA and the MHT can be found in [227, 228], respectively.

Both the JPDA and the MHT have been fundamental building blocks for the future development in MTT, leading to more sophisticated solutions. Most important developments include the interacting multiple model (IMM) filtering [229] to track manoeuvring targets, the variable structure IMM [230] to incorporate additional prior information in the tracking algorithm, the capability to deal with unresolved targets [231], and the random matrix framework to track extended targets [232]. A quantitative comparison among the MTT strategies is provided in [233].

MTT methods, like JPDA and MHT, are based on conventional probability theory [226, 234]. A more recent class of methods is based on finite set statistic (FISST) [235–238]. Here, target states and measurements are modelled as random finite sets (RFSs), which means that they have no order and also their number is modelled as an unknown random variable. RFS methods facilitate the modelling of target appearance and disappearance in a Bayesian setting; however, they typically perform approximations based on rather non-intuitive quantities. A Bayesian filtering solution, the probability hypothesis density (PHD) filter [235], is proposed in which the first-order statistical moment of the multitarget posterior is propagated instead of the full posterior

Table 2 Comparison in terms of ToT and FAR ($s^{-1}km^{-2}$) of DIFFUSION, local tracking algorithm (MHT), and local detector. The CER is the percentage of expected communication failures. In POMA 2012, a Bayesian multisensor tracking algorithm is considered at Harpo and Groucho with 75% of CER and with no communication errors. In POMA 2013, T2T fusion is considered with no communication errors. The parameter γ is a score that is used to confirm new track candidates

	POMA datasets							
	2012				2013			
	Method	CER	FAR	ToT %	Method	γ	FAR	ToT %
Harpo	Detector	—	7.5×10^{-5}	78	MHT	—	1.6×10^{-5}	83
Groucho	Detector	—	9.1×10^{-5}	53	MHT	—	1.2×10^{-5}	70
DIFFUSION	RFS Harpo	75%	5.8×10^{-7}	95	T2T	0	0.9×10^{-5}	92
DIFFUSION	RFS Groucho	75%	6.7×10^{-7}	91	T2T	1	1.3×10^{-7}	85
DIFFUSION	RFS	0	2.5×10^{-7}	94	T2T	2	6.4×10^{-8}	78

distribution. The PHD is the function whose integral in any region of the state space is the expected number of targets in that region. The PHD filter and its extension, the cardinalised PHD (CPHD) [239] filter are gaining increased popularity in the MTT community and have led to many different derivations, interpretations and implementations [236, 238]. Further developed in the RFSs framework include the multi-Bernoulli filter [240] and the labelled multi-Bernoulli filter [241, 242]. Another important building block for both the classical MTT and RFSs-based MTT are sequential Monte-Carlo (SMC) methods [243, 244]. The SMC methods provide a computationally efficient solution for sampling probability distributions of time-varying random states. They enable the development of MTT algorithms for non-linear non-Gaussian motion and measurement models.

Many MTT methods are computationally demanding and their complexity does not scale well in the number of targets and other relevant system parameters. Thus, they are often impractical for use on resource-limited devices. MTT algorithms with low complexity and good scalability can be obtained by using the methodology of BP. BP can provide a principled approximation of optimum Bayesian inference that achieves a very attractive performance-complexity compromise [245, 246]. However, only recent works have considered its use for MTT [207, 247–252]. Using BP for MTT is promising due to the highly efficient solution of the data association problem combined with sequential Monte-Carlo techniques and is potentially suitable for arbitrary non-linear and non-Gaussian problems. Owing to their low complexity and good scalability, BP-based methods are also suitable for large-scale tracking scenarios involving a large number of targets and/or sensors and/or measurements, and for use on resource-limited devices, such as on-board an AUV.

Another important aspect of the problem is the definition of suitable performance metrics and benchmarks. There exists a large variety of metrics for the MTT problem, such as the time-on-target (ToT) (per cent of time steps where targets in the surveillance area are correctly declared present) and the false-alarm rate (FAR) (normalised number of false tracks or contacts) [253, 254]. ToT and FAR only take into account detection errors. Other metrics such as the mean square error [255, 256] are only related to errors in state estimation. The recently proposed optimal subpattern assignment [257] metric can take both detection and estimation errors into account.

Mathematically, the MTT problem is twofold in the sense that it consists of detection and estimation. It can be summarised as follows: let $\mathcal{X}_k = \{\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(N_k)}\}$ be the unknown state of all N_k targets at time k and $\mathcal{Z}_{k,s} = \{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(M_{k,s})}\}$ be the set of $M_{k,s}$ measurements generated by sensor s at time k. Based on the measurements $\mathcal{Z}_{k,s}$ provided by all sensors s up to time k, the model of the sensor $f(\mathcal{Z}_{k,s}|\mathcal{X}_k)$, and the model of the target $f(\mathcal{X}_k|\mathcal{X}_{k-1})$ we want to

i. detect the number of targets $\hat{N}_k$;

ii. estimate their state $\hat{\mathcal{X}}_k \triangleq [\hat{\boldsymbol{x}}_k^{(1)\mathrm{T}} \cdots \hat{\boldsymbol{x}}_k^{(\hat{N}_k)\mathrm{T}}]^{\mathrm{T}}$.

Due to the high computational complexity related to evaluating the model of the sensor suffering from MOU, approximations have to be made in order to obtain a feasible solution for the MTT problem. Different approximations lead to different tracking algorithms. For instance, the JPDA calculates the number of targets using a heuristic track logic and assumes that the marginal posterior (and prior) of each target is Gaussian [221]. The PHD and the CPHD filter approximate the RFS related to $\boldsymbol{x}_k$ by its expected value [235]. The belief propagation tracker (BPT) [207, 252] computes approximate marginal posterior PDFs for each element in $\mathcal{X}_k$.

4.1 Distributed information fusion in cooperative robotic networks

Sharing local information among the AUVs and/or with a fusion centre (FC) is one of the key aspects for an improved target detection and tracking performance in cooperative robotic networks. Two main schemes have been proposed in [258], in which the information shared among AUVs consists of (i) measurements $\boldsymbol{z}_{k,s}$, generated by the local detectors at each vehicle and (ii) tracks generated by local tracking algorithms at each vehicle. In the first scheme, measurements are fused in a Bayesian multisensor tracking algorithm, adopting a single Bernoulli RFS formulation [258, 259] or a BP formulation [207, 260]. In the second scheme, tracks already created by local tracking algorithms are combined using the track-to-track (T2T) association and fusion procedure [258]. These schemes are often referred to as DIFFUSION strategies [258]. It is worthwhile to note that the number of publications in the open literature that report underwater surveillance results using real-world measurements is very limited.

The performance of different information fusion schemes was investigated in [207, 258] in post-processing using measurements collected by the NATO Science and Technology Organization – CMRE during the exercises *Proud Manta (POMA)* in 2012 and 2013 and the *LCAS* sea trial in 2015. In the considered datasets, an echo-repeater towed by a ship simulated a target with high target strength. The measurements were provided by the cooperative robotic network for underwater surveillance operated at CMRE, deployed with one acoustic source and two receiver sensors. The receivers were hydrophone arrays towed by two AUVs (Harpo and Groucho).

Results based on POMA 12 and 13 datasets are reported in Table 2 (see also [258]). It is shown that information fusion can lead to a significantly improved tracking performance compared to the case where measurements of a single AUV are considered. Specifically information fusion can increase the ToT and at the same time reduce the FAR by two orders of magnitudes. Furthermore, the robustness against communication errors was investigated by simulating different communication failures [258]. In particular, we simulated measurements collected by an AUV not being received by the other AUV at certain time steps and quantified this error by the communication error rate (CER) [258].

Recently, the BPT approach [207, 252] was applied to an LCAS dataset with a very high number of false alarms, see Figs. 9*a* and *b*. Due to information sharing (detections) among AUVs, the target can be detected and tracked reliably by BPT, despite the high number of false alarms (see Fig. 9*c*). A comparison with the distributed MHT [261, 262], which is a state-of-the-art algorithm for underwater surveillance is provided in Fig. 9*d*. The improved ToT versus FAR trade-off of the BPT compared to the MHT is related to a Bayesian optimum strategy for fusing measurements from different AUVs. Note that in these results it is assumed that all collected measurements can be exchanged by the AUVs, which is infeasible in practice due to bandwidth and delay limitations of the underwater communication channel. However, these results show potential gains related to information fusion in cooperative robotic networks for underwater surveillance.

4.2 Challenges of MTT for underwater surveillance

As demonstrated in the previous subsection, the use of multiple AUVs can lead to a significantly improved detection and tracking performance in MTT for underwater surveillance. However, while many spatially distributed AUVs and many measurements per AUV are desirable for MTT in order to increase target detection probability and estimation accuracy, both network size and data rates are limited by the challenging underwater communication channel. Therefore, there is a need for smart distributed inference architectures that enable MTT performance gains related to cooperative robotic networks in real time.

As suggested in [263, 264], existing architectures for distributed inference can be broadly classified into three different classes. The first class considers that all local measurements of the AUVs are collected by an FC [265–267], which then performs the inference task. Either all AUVs are able to directly communicate with the FC or communication is performed over multiple hops. Therefore, algorithms in this class do not scale well with the size of the networks. The information fusion algorithms discussed in the previous Section 4.1 belong to this first class.

In the second class of architectures, there is no FC and AUVs can communicate only with neighbouring AUVs. AUVs operate in two phases. In the sensing phase, each AUV collects observations from the environment over a sufficiently long period of time. Subsequently, in the communication phase, AUVs exchange information iteratively with their neighbours and run a consensus algorithm to arrive at a globally optimum solution [268].

A third class of architectures for distributed inference in which sensing and communication phases can also overlap, i.e. sensing and communication occur simultaneously, has recently been proposed [269–271]. This third class is suitable for networks that are able to adapt and to react to the possible changes in the state of interest [272–274]. Algorithms from this class seem to be promising for the MTT problem in which the number of targets and their states are time-varying. A special case of this class are distributed filtering algorithms based on consensus [275–277], which have recently been applied to the MTT problem [278, 279].

Unfortunately, all existing fully distributed MTT algorithms are not suitable for underwater surveillance using cooperative robotic networks. For instance, in [277], iterative consensus schemes are employed in order to calculate the joint likelihood function using only local communication among AUVs. In an underwater surveillance scenario, this would mean that multiple packet exchanges need to be performed among AUVs for each pulse repetition interval of the sonar transmitter, which is not feasible due to the limited communication bandwidth. Other existing distributed filtering solutions have similar communication-related implications. The design of a fully distributed inference architecture for MTT in the challenging underwater communication channel therefore remains an open research problem.

5 Underwater communications

As discussed above, cooperative robotic networks require frequent exchange of information. Relying on acoustic waves for ranges beyond tens of meters, several factors affect the communications performance such as limited bandwidth due to frequency-dependent absorption loss, multipath propagation, Doppler spread and long propagation delays due to the sound speed in water. There is no universal underwater acoustic channel since every communications link has unique operating parameters (ocean depth, transmitter/receiver depth, sea-surface wave-height, sea-bottom composition, sound speed variation, to name a few). Due to the complexities of the underwater environment, it is very tedious to find a representative channel fading model. This implies that a coded modulation (physical-layer) scheme optimally designed for a specific fading model (e.g. Rayleigh fading) will become suboptimal when the environment changes [280]. This is in stark contrast with mobile radio channels where standardised models exist such as the family of IEEE 802 models. Consequently, current technology does not support interoperability for distributed sensing since different stakeholders develop their systems based on rigid, closed, proprietary all-in-one implementations of acoustic modems and protocol stacks. Commercial acoustic modems [281] can provide about 30 kbps data transfer in vertical links where the multipath propagation is not significant. However, performance reduces to 1 kbps or less in horizontal links where the multipath becomes substantially long. In what follows, we describe the main achievements obtained by the research community within the framework of interoperability, physical layer, networking protocols and hybrid solutions. Security aspects, together with current trends and future works are discussed as well.

5.1 Interoperability solutions

One of the first efforts on standardisation and interoperability at the higher layers of the protocol stack is presented in [282] where the underwater network architecture is defined. This initiative joins together institutions from the US and Singapore in defining an OSI-like protocol stack tailored to the specific needs of underwater networks. Other contributions have been proposed in the recent past highlighting the need to develop next generation of underwater acoustic networks (UANs) based on software-defined solutions with the support for intense cross-layering data exchange [283, 284].

To demonstrate the market requirements for underwater systems interoperability, an international oil and gas industry network has established the subsea wireless group (SWiG) [285]. The SWiG has as primary objective to promote interoperability for subsea wireless communications. Other objectives of the SWIG include identifying areas where standards need to be developed for the industry in the underwater domain and promoting best practices across the industry.

CMRE has developed, in collaboration with academia and industry, a physical-layer communication scheme, called JANUS [30], which has been recently promulgated as NATO standard (STANAG) [286]. JANUS is the first underwater digital communications standard to be agreed internationally. It is publicly available and free for civilian and military users. JANUS is based on frequency-hopping binary frequency shift keying with tunable centre frequency and bandwidth. If the default 9400–13,600 Hz band is chosen, the resulting bit rate is 80 bps. Characteristic applications of JANUS are the transmission of automatic identification system and meteorological and oceanographic data to submerged assets [287, 288]. The objective is to use a standardised solution to increase the maritime situational awareness and to improve safety and water-space management between manned and unmanned surface and underwater assets, including swarms of cooperative robots.

5.2 Physical-layer solutions

The physical layer of the communication stack defines the coded modulation (and hence the data rate) for transmission of raw bits as well as the signal processing method employed at the receiver for recovering the transmitted bits. In surveillance applications, data rates of about hundreds of bits per second are typically sufficient for control and command (e.g. status information, navigation) signals between robots with the stringent requirement that the bit error rate must be very low (about 10^{-6}). Frequency shift keying (FSK) modulation with energy detection is typically favoured for this type of application scenarios since it can robustly cope with multipath and Doppler of the received signal. In addition, FSK

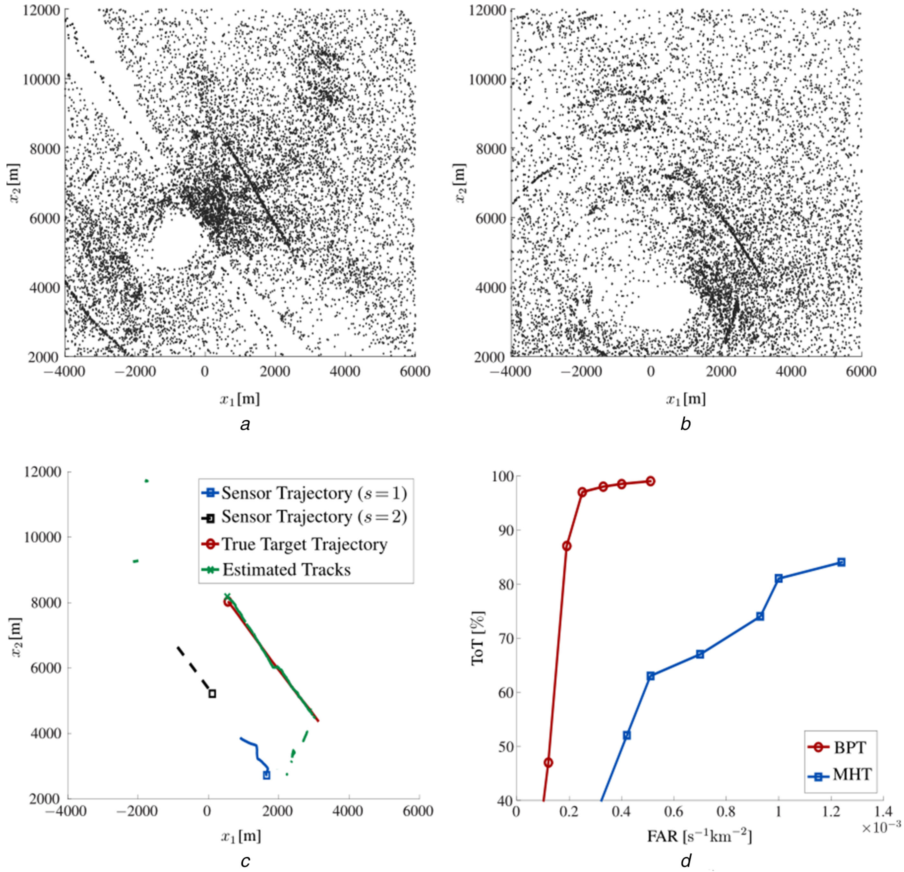


Fig. 9 *Dataset from the LCAS15 sea trail*
(a) Measurements collected by the first, ***(b)*** The second AUV. ***(c)*** Comparison of the multisensor BPT [207, 252] with the distributed MHT [261, 262] in terms of ToT versus FAR. ***(d)*** Estimated tracks from multisensor BPT and trajectories of the AUVs and the target. Despite the high number of false alarms, the BPT can reliably track the target

systems can be efficiently realised in hardware using DFT-based filters. Note that robust performance and ease of implementation come at the expense of low spectral efficiency (not higher than 0.5 bits/s/Hz). Representative FSK systems can be found in [289, 290]. Reported results indicate data rates from few bps to 2 kbps over ranges of 5–10 km in various environments.

In scenarios where data collected from sonars or other robotic sensors (e.g. camera) must be exchanged between robots for mission improvement, it is required a transmission rate of tens to hundreds kilobits per second with a bit error rate requirement of about 10^{-3}. In such a case, bandwidth-efficient techniques based on phase-coherent modulation such as phase-shift keying (PSK) and quadrature amplitude modulation are needed. An intermediate solution between FSK and PSK methods is differential phase-shift keying (DPSK). DPSK enjoys simpler carrier recovery than PSK, however, it suffers from higher errors for the same data rate. Nevertheless, both PSK and DPSK are highly sensitive to channel multipath conditions and a precipitous non-linear degradation occurs in the face of environmental mismatch. Dealing with multipath impairments and mobility to achieve high data rates are one of the most challenging goals in underwater acoustic communications. As this is still an active research area, a plethora of coherent systems have been developed and deployed in various shallow and deep water environments [289–291]. Popular signal processing methods include equalisation, orthogonal frequency division multiplexing, time reversal and their extensions to MIMO systems. Reported results vary from 48 kbps over 2 km to 120 kbps over ranges up to 80 m.

5.3 Network protocol solutions

Due to the challenges posed by the communication channel, underwater networking is currently a very active area of research. Particular importance is given to the design of new medium access control (MAC) and routing protocols that account for the high propagation delays, the low bandwidth available and the many challenges posed by the acoustic signal propagation [290]. Distributed and *ad hoc* solutions are of particular interest to cope with the dynamics of the acoustic medium, which can change in space and time, and with the presence of mobile assets changing the network topology over time. The support of mobility is of great importance, since it enables operation in areas where no infrastructure has been deployed and to enlarge the area of operations if required.

Recently, several underwater MAC protocols have been investigated considering different potential approaches [292]: time division multiple access (TDMA), frequency division multiple access (FDMA), CDMA, carrier sense multiple access (CSMA), medium access collision avoidance (MACA), and hybrid schemes.

TDMA protocols could represent the most suitable option for small and static networks, but node synchronisation is required. Additionally, in the presence of mobile assets, TDMA approaches do not scale well with the network size. FDMA solutions are usually not very efficient in underwater networks due to the limited available bandwidth. CDMA is therefore often favoured over TDMA and FDMA when a decrease in point-to-point data rates due to code spreading is admissible. Additionally, many CSMA and MACA solutions have been proposed assuming a light, medium or heavy use of control information to reserve the underwater acoustic channel [293]. It has been shown that, depending on the network configuration, the environment and the quality of the channel, different solutions should be preferred and adaptive approaches should be considered [294].

Various routing protocols have been also proposed for UANs [295, 296]. Geographic and hop-by-hop based, depth-based (for scenarios with the data collection points placed on the surface), flooding-based, source-path based, and multi-point relay protocols. Recent trends in protocol design have shown that cross-layer techniques can impact protocol performance positively, especially in networks with limited resources and/or deployed in challenging environments, like UANs [297]. Various underwater cross-layer solutions have therefore been implemented for underwater acoustic

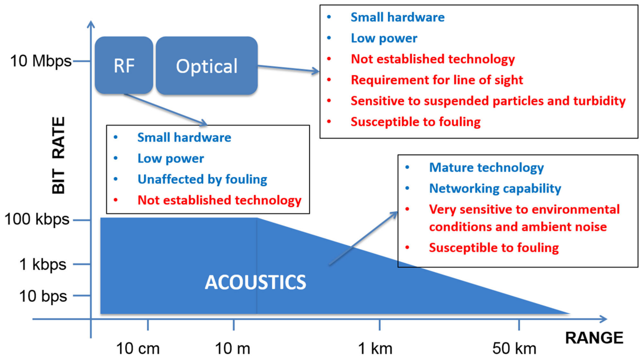


Fig. 10 *Characteristics in terms of achievable range and bit rate of the various communication interfaces in the underwater domain*

networks. A performance comparison based on simulation and experimental data can be found in [298]. To reduce the overhead introduced in the network various solutions have been proposed combining cross-layer networking functionalities with services required by mobile vehicles, such as localisation and synchronisation [104, 299].

Delay-tolerant networking (DTN) [300] solutions have been also addressed in the contest of underwater networks [301]. Work on DTN was initially motivated by problems in planetary-scale networking for space exploration, but to a large extent the same problems of large propagation delays and occlusion in shadow zones are also relevant in underwater communications. As a general rule, DTNs forward data opportunistically, typically exploiting the mobility of nodes to have packets routed to otherwise unreachable portions of the network.

From this wide spectrum of solutions, it is plausible to argue that there is no solution fitting all the possible scenarios, since the communication parameters (intrinsic and channel) may significantly vary in space and time. Depending on the specific surveillance application, on the network topology and on the channel condition, a different selection and combination of MAC and routing protocols may be needed to meet the quality of service requirements in terms of delay in the data delivery, throughput, and packet delivery ratio. The possibility to remotely reconfigure and adapt the protocol stack to use [302] would be very welcome.

5.4 Hybrid solutions

Acoustic waves is the default way to convey information wirelessly in underwater environments; however, the need for very high-speed communications has triggered the investigation of RF and optical communications. RF, optical, and acoustic links are characterised by very different achievable ranges and bit rates. These characteristics are summarised in Fig. 10.

One scenario that drives this need is the docking of AUVs in underwater stations for charging and data transfer. Having underwater stations significantly prolongs mission duration since the time spent to recover and redeploy the vehicle is minimised. RF underwater could aid in precisely positioning the vehicle inside the confined area of the docking station as well as to exchange vast amounts of data with the base station. Another driver for very high-speed communications is data muling systems. Such systems facilitate the collection of data from remote sensors without the need to physically connect with them. This can happen by using a mobile robot that swims near the sensor and downloads the data using optical communications.

Despite underwater optical communications being a young field of scientific research, various modem developments from different research groups have been reported. The study in [303] reported a data rate of 5 Mbps for ranges of 100–200 m in very clear deep ocean. In [304], the fastest achievable rate reported was 2 Mbps at 50 m in a swimming pool. Another notable system was presented in [305] where the authors claim an achievable rate of 58 Mbps in an outdoor water tank of 2.5 m with strong sunlight disturbance. RF communications is a rapidly growing area as well. Compared to optics, RF is not susceptible to turbidity and fouling and can provide about 100 Mbps at very short distances (<1 m) [306]. A hot topic currently is to implement IEEE 802.11 networks in underwater with the aid of software-defined radios [307].

EM, optics, and acoustics are viewed as complementary solutions since there is little overlap in their operational mechanisms. Consequently, hybrid underwater communication systems are the way forward to maximising performance in underwater data transfers. Indicative examples of such hybrid implementations are presented in [308, 309]. The application of high data rate and low latency links (such as the ones offered by optical communications) open the way for applications such as physically detached and re-shapeable distributed sensors. An example of such potential applications is detached acoustic antennas that can use high data rate, low latency links to exchange acoustic data and coordinate their relative positioning, exploiting acoustic signal coherence. A simulation study is presented in [310].

5.5 Security solutions

The broadcast nature of the underwater acoustic channel allows an attacker to jam or intercept communications in a robotic network. Part of the success for achieving reliable and secure underwater communications relies on the nature of the transmitted signal. Following the paradigm of radio communications, sophisticated modulation techniques employing spread spectrum (SS) signals can be used to give the communications receiver an advantage against jammers [311, 312]. The same SS signals have the inherent ability to provide covertness, i.e. low probability of intercept/detection (LPI/LPD) characteristics due to their low-level transmit power densities.

Cryptographic keys handled by upper-network-layers are typically used for security of information (authentication, confidentiality, and privacy). Unfortunately, these types of crypto keys induce an overhead in the message, which comes at a high price in underwater robotic networks due to the severely limited bandwidth. An interesting concept, termed as physical-layer security [313], indicates that noise and channel fading can be exploited for 'covert' communications, without requiring the usage of an additional secret key. In the underwater domain, the authors in [314] exploit the received signal strength for secret key generation. Another example is [315] where a protocol that generates secret keys dynamically based on the channel frequency response is proposed.

Although physical-layer security solutions can be used to ensure confidentiality on the communication link, various denial of service attacks can be still conducted to impair the performance of a network of collaborative nodes. Jamming, spoofing, and packet manipulation and redirection (just to name a few) can be effectively applied to impair the navigation and localisation capabilities of mobile robots. These are critical capabilities which have to be ensured in order to correctly accomplish the requested tasks. One recent attempt to tackle the security problem at different network levels is presented in [316], where the authors propose a security suite specifically designed for underwater acoustic networks. The security components are a secure routing protocol and a set of cryptographic primitives aimed at protecting the confidentiality and the integrity of the communications. The approach was integrated into a deployed network during the UAN11 sea trials of the European funded FP7 UAN Project [6].

While a network of cooperative robots is vulnerable to various attacks, the use of node cooperation and mobility can be effectively used to react to these attacks by adapting the network geometry similarly to what has been described in [70]. Different strategies can be explored to allow mobile nodes to cover connectivity holes in the network, to increase the quality of the communication links and to avoid the presence of single points of failure. Similarly, the use of a hybrid communication system can be considered as well in order to select the best communication interface to use, according to the current network geometry and on-going attack.

5.6 Current trends and future works

From the above discussion, a promising way forward is to abandon existing monolithic integrated modems and develop software-

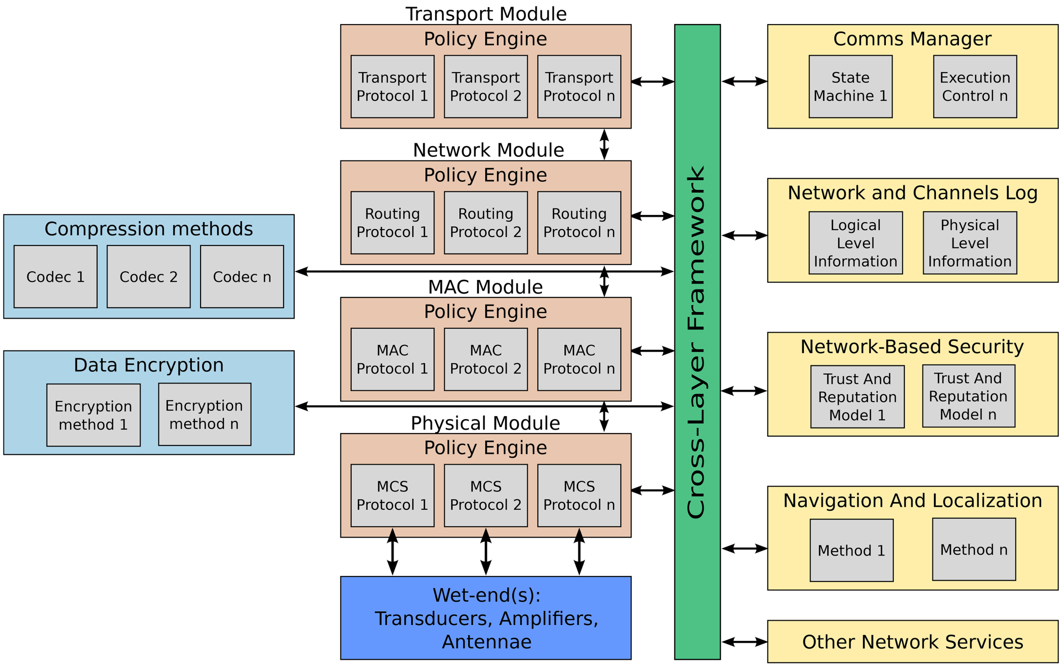


Fig. 11 *Next generation underwater networking architecture, as proposed in [283]*

defined open-architecture communication stacks. The study in [283, 284, 317] proposes the use of (i) a software-defined approach with intense use of cross-layer messages, (ii) the use of context awareness and adaptive trust and reputation models, and (iii) node cooperation and mobility. Although interesting guidelines are presented towards the deployment of secure and robust underwater networks, no implementation, at-sea testing and validation of the proposed solutions are provided.

Recently, software-defined solutions with the support of cross-layering data exchange and hybrid communications have been published [283, 284]. Fig. 11 displays the networking architecture presented in [283]. The presence of a software-defined component (policy engine), which selects different protocol implementations (from coded modulation to routing and application support) can be seen. Cross-layering information is used in support to the decision-making process. For example, based on the work in [318], selecting the most appropriate modulation and coding scheme given the specific channel conditions is possible. This physical-layer information can be provided to upper layers to adjust the use of control messages and the selection of the next node to follow for data delivery. Similarly, upper layers can share quality of service data, e.g. message priority and maximum delivery time, to drive the selection of lower layers parameters in selecting the best waveform, error correction coding and encryption solution to use.

The field of underwater communications is rapidly moving towards exchanging data from heterogeneous systems in order to provide more general and complex services to end-users. Towards this end, the development of modular communication stacks with the ability to adapt to the environment, counteract security attacks, switch between different modalities (optics or radio), and sustainably manage the underwater network for long-lasting operations is a wide open research problem.

6 Conclusions

A review of recent advances in cooperative robotic networks for underwater surveillance has been presented. To this aim, the underwater surveillance scenario has been divided into four main research areas: (i) underwater robotics, (ii) acoustic signal processing, (iii) tracking and distributed information fusion, and (iv) underwater communications networks. For each area, we overviewed the main challenges and highlighted some areas for future work in the field. Thanks to the ever rising power and computational abilities, today's robots can be deployed in networks so that when properly interconnected can form adaptive and intelligent systems capable of unprecedented level of scalability, robustness, and adaptability. The peculiarities of the underwater environment have been outlined, and we highlighted the constraints that they put on the development of robotic networks. The impressive recent development of underwater communications has represented a key enabler to fostering the further deployment of autonomous sensor networks where robots can make collective decisions, share relevant data in a secure manner, and fuse information together to achieve a network gain. In parallel, sonar signal processing, the main sensor modality for underwater surveillance, can today exploit new waveforms thanks to availability of new transducers with larger dynamic ranges. At the same time the available computational power available on today's embedded computers allows to use quite advanced algorithms, able to bridge the sensors with the more complex adaptive vehicle behaviours. Real-world operation of robotic networks is on the verge of a paradigm shift, and it seems easy to envision multiple robotic networks to be deployed in the coming years. At the same time, there are still multiple research challenges that need to be addressed to reach the necessary maturity for the robust operation of robotics surveillance systems. More in particular, two main points still need to be tackled. First, a tighter integration of the cross-disciplinary methodologies and topics presented herein driven by a system-of-system approach. Second, a stronger effort in the industrial world and in the interested end-users to narrow the gap between technology evolution and user adoption in real-world applications is presented.

7. Acknowledgment

This work was supported by NATO ACT under the CASW Programme of Work.

References

[1] Zimmer, W.M.X.: '*Passive acoustic monitoring of cetaceans*' (Cambridge University Press, Cambridge, 2011). Available at https://www.cambridge.org/core/books/passive-acoustic-monitoring-of-cetaceans/8D59083194B2634B9F490635EAF23653

[2] Polmar, N., Whitman, E.: '*Hunters and killers: volume 2: anti-submarine warfare from 1943*' (Naval Institute Press, 2016)

[3] Williams, D., Couillard, M.: 'Efficient dense sonar surveys with an autonomous underwater vehicle'. Proc. 11th European Conf. on Underwater Acoustics (ECUA), 2012

[4] Cresta, M., Storti, E., Simetti, E., *et al.*: 'Archimede: integrated network-centric harbour protection system'. 2010 Int. WaterSide Security Conf., November 2010, pp. 1–4

[5] Caiti, A., Munafò, A., Vettori, G.: 'A geographical information system (GIS)-based simulation tool to assess civilian harbor protection levels', *IEEE J. Ocean. Eng.*, 2012, **37**, (1), pp. 85–102

[6] Caiti, A., Calabrò, V., Andrea, M., *et al.*: 'Mobile underwater sensor networks for protection and security: field experience at the UAN11 experiment', *J. Field Robot.*, 2013, **30**, (2), pp. 237–253. Available at http://dx.doi.org/10.1002/rob.21447

[7] 'The navy unmanned undersea vehicle UUV master plan'. Technical Report, US Navy, 2004

[8] Nootz, G., Jarosz, E., Dalgleish, F., *et al.*: 'Quantification of optical turbulence in the ocean and its effects on beam propagation', *Appl. Opt.*, 2016, **55**, (31), pp. 8813–8820

[9] Karagianni, E.A.: 'Electromagnetic waves under sea: bow-tie antenna design for Wi-Fi underwater communications', *Prog. Electromagn. Res.*, 2015, **41**, p. 189198

[10] Gerken, L.: '*ASW versus submarine technology battle*' (A. S. Corp, Ed., 1987)

[11] Stojanovic, M.: 'On the relationship between capacity and distance in an underwater acoustic communication channel'. Proc. 1st ACM Int. Workshop on Underwater Networks, ser. WUWNet '06, New York, NY, USA, 2006, pp. 41–47. doi: 10.1145/1161039.1161049

[12] Caiti, A., Munafò, A., Vettori, G.: 'System performance tradeoff in underwater harbour protection'. Proc. UAM 2009, 2009

[13] Howard, J.: 'Fixed sonar systems: the history and future of the underwater silent sentinel', *Submar. Rev.*, 2011, pp. 1–12

[14] Stommel, H.: 'The Slocum mission', *Oceanography*, 1989, **2**, pp. 22–25

[15] Curtin, T., Bellingham, J., Catipovic, J., *et al.*: 'Autonomous oceanographic sampling networks', *Oceanography*, 1993, **6**, pp. 86–94. doi.org/10.5670/oceanog.1993.03

[16] 'Background links for ups experiment (underwater persistent surveillence)', Available at http://www3.mbari.org/MB2006/UPS/mb2006-ups-links.htm, accessed 11 May 2017

[17] Webb, D.C., Simonetti, P.J., Jones, C.P.: 'SLOCUM: an underwater glider propelled by environmental energy', *IEEE J. Ocean. Eng.*, 2001, **26**, (4), pp. 447–452

[18] Eriksen, C.C., Osse, T.J., Light, R.D., *et al.*: 'Seaglider: a long-range autonomous underwater vehicle for oceanographic research', *IEEE J. Ocean. Eng.*, 2001, **26**, (4), pp. 424–436

[19] Fossum, T.: 'Intelligent autonomous underwater vehicles'. Technical Report, Norwegian University of Science and Technology, 2016

[20] Topal, S., Erkmen, I., Erkmen, A.: 'Towards the robotic avatar: an extensive survey of the cooperation between and within networked mobile sensors', *Future Internet*, 2010, **2**, pp. 363–387

[21] Hughes, D.T., Baralli, F., Kemna, S., *et al.*: 'Collaborative multistatic ASW using AUVs: demonstrating necessary technologies'. Technical Report, Nato Undersea Research Centre, 2009

[22] Ferri, G., Munafò, A., Goldhahn, R., *et al.*: 'Results from COLLAB13 sea trial on tracking underwater targets with AUVs in bistatic sonar scenarios'. Oceans – St. John's, 2014, September 2014, pp. 1–9

[23] Munafò, A., Ferri, G.: 'An acoustic network navigation system', *J. Field Robot.*, 2017, pp. 1–20

[24] LePage, K.D., Goldhahn, R., Alves, J., *et al.*: 'Autonomous networked antisubmarine warfare research and development at CMRE'. OCEANS 2015 – Genova, May 2015, pp. 1–6

[25] http://liquidr.com/

[26] Bellingham, J.: '*Handbook of ocean engineering*' (Springer Dordrecht Heidelberg London New York, 2016), ch. Autonomous Underwater Vehicle Docking, pp. 387–422

[27] Martin, A.Y.: 'Unmanned maritime vehicles: Technology evolution and implications', *J. Mar. Technol. Soc.*, 2013, **47**, (5), pp. 72–83

[28] Schmidt, H., Benjamin, M., Petillo, S., *et al.*: '*Handbook of ocean engineering*' (Springer Dordrecht Heidelberg London New York, 2016), ch. Nested autonomy for distributed ocean sensing, pp. 459–479

[29] Li, X., Martinez, J., Rodriguez-Molina, J., *et al.*: 'A survey on intermediation architectures for underwater robotics', 2016

[30] Potter, J.R., Alves, J., Green, D., *et al.*: 'The JANUS underwater communications standard'. Proc. 2nd IEEE OES Int. Conf. on Underwater Communications and Networking, ser. UComms'14, Sestri Levante, Italy, 3–5 September 2014

[31] Waite, A.: '*SONAR for practising engineers*' (Wiley, 2002, 3rd edn.)

[32] Paull, L., Saeedi, S., Seto, M., *et al.*: 'AUV navigation and localization: a review', *IEEE J. Ocean. Eng.*, 2014, **39**, (1), pp. 131–149

[33] Burgard, W., Moors, M., Stachniss, C., *et al.*: 'Coordinated multi-robot exploration', *IEEE Trans. Robot.*, 2005, **21**, (3), pp. 376–386

[34] Hollinger, G., Sukhatme, G.: 'Sampling-based robotic information gathering algorithms', *Int. J. Robot. Res.*, 2014, **33**, (9), pp. 1271–1287

[35] Portugal, D., Rocha, R.: 'A survey on multi-robot patrolling algorithms'. Proc. Second IFIP WG 5.5/SOCOLNET Doctoral Conf. Computing, Electrical and Industrial Systems, DoCEIS 2011, Costa de Caparica, Portugal, 21–23 February 2011

[36] Antonelli, G., Arrichiello, F., Casalino, G., *et al.*: '*Harbour protection strategies with multiple autonomous marine vehicles*' (Springer International Publishing, Cham, 2014), pp. 241–261. doi: 10.1007/978-3-319-13823-722

[37] Sildam, J., LePage, K., Braca, P., *et al.*: 'On unsupervised track classification based on entropy distribution estimated along track related detections'. 1st Int. Conf. and Exhibition on Underwater Acoustics, Corfu, Greece, 2013

[38] Sinha, A., Ding, Z., Kirubarajan, T., *et al.*: 'Track quality based multitarget tracking approach for global nearest-neighbor association', *IEEE Trans. Aerosp. Electron. Syst.*, 2012, **48**, (2), pp. 1179–1191

[39] Ferri, G., Munafò, A., Goldhahn, R., *et al.*: 'Towards fully autonomous underwater vehicles in ASW scenarios: an adaptive, data driven AUV mission manager layer'. OCEANS 2015, Genova, Italy, 18–21 May 2015

[40] Ferri, G., Djapic, V.: 'Adaptive mission planning for cooperative autonomous maritime vehicles'. 2013 IEEE Int. Conf. on Robotics and Automation, May 2013, pp. 5586–5592

[41] Kemna, S., Hamilton, M.J., Hughes, D.T., *et al.*: 'Adaptive autonomous underwater vehicles for littoral surveillance: the GLINT10 field trial results', *Intelligent service robotics*, 2011, **4**, (4), pp. 245–258

[42] Ferri, G., Munafò, A., Goldhahn, R., *et al.*: 'A non-myopic, receding horizon control strategy for an AUV to track an underwater target in a bistatic sonar scenario'. Proc. CDC2014, Los Angeles, 15–17 December 2014

[43] Murphy, R.: '*Introduction to AI robotics*' (MIT Press, 2000)

[44] Rajan, K.: 'The role of deliberation (and AI) in marine robots'. Workshop on Marine Robotics: Looking into the Crystal Ball, Eurocast 2013, Gran Canaria, Spain, 11–13 February 2013

[45] Wynn, R.B., Huvenne, V.A., Bas, T.P.L., *et al.*: 'Autonomous underwater vehicles (AUVs): their past, present and future contributions to the advancement of marine geoscience', *Mar. Geol.*, 2014, **352**, pp. 451–468, 50th Anniversary Special Issue. Available at http://www.sciencedirect.com/science/article/pii/S0025322714000747

[46] Munafò, A., Simetti, E., Turetta, A., *et al.*: 'Autonomous underwater vehicle teams for adaptive ocean sampling: a data-driven approach', *Ocean Dyn.*, 2011, **61**, (11), p. 19811994. doi: 10.1007/s10236-011-0464-x

[47] Pebody, M.: 'Autonomous underwater vehicle collision avoidance for under-ice exploration', *Proc. IME M J. Eng. Marit. Environ.*, 2009, **222**, pp. 53–66

[48] McPhail, S.: 'Autosub6000: a deep diving long range AUV', *J. Bionic Eng.*, 2009, **6**, pp. 55–62

[49] German, C., Yoerger, D., Jakuba, M., *et al.*: 'Hydrothermal exploration with the Autonomous Benthic Explorer', *Deep Sea Res.*, 2008, **I, 55**, pp. 203–219

[50] Shafer, A.J., Benjamin, M.R., Leonard, J.J., *et al.*: 'Autonomous cooperation of heterogeneous platforms for sea-based search tasks'. OCEANS 2008, September 2008, pp. 1–10

[51] Brito, M.P., Griffiths, G.: '*Handbook of ocean engineering*' (Springer Dordrecht Heidelberg London New York, 2016), ch. Autonomy: risk assessment, pp. 4527–4543

[52] Burian, E., Yoerger, D., Bradley, A., *et al.*: 'Gradient search with autonomous underwater vehicles using scalar measurements'. Proc. AUV 96, Monterey, CA, USA, 1996, pp. 86–98

[53] Li, W., Farrell, J., Pang, S., *et al.*: 'Moth-inspired chemical plume tracing on an autonomous underwater vehicle', *IEEE Trans. Robot.*, 2006, **22**, (2), pp. 292–307

[54] Ferri, G., Munafò, A., Alves, J., *et al.*: 'A data-driven control strategy in synergy with continuous active sonar for littoral underwater surveillance'. OCEANS 2016 MTS/IEEE Monterey, September 2016, pp. 1–7

[55] Ferri, G., Jakuba, M., Yoerger, D.: 'A novel trigger-based method for hydrothermal vents prospecting using an autonomous underwater robot', *Auton. Robots*, 2010, **29**, (1), pp. 67–83

[56] Alvarez, A., Mourre, B.: 'Optimum sampling designs for a glider-mooring observing network', *J. Atmos. Oceanic Technol.*, 2012, **29**, pp. 601–612

[57] Lermusiaux, P., Tapovan, L., Haley, P., *et al.*: '*Handbook of ocean engineering*' (Springer Dordrecht Heidelberg London New York, 2016), ch. Science of autonomy: Time-Optimal Path Planning and Adaptive Sampling for Swarms of Ocean Vehicles

[58] Hero, A.O., Cochran, D.: 'Sensor management: past, present, and future', *IEEE Sens. J.*, 2011, **11**, (12), pp. 3064–3075

[59] Dias, M., Stentz, A.: 'A market approach to multirobot coordination'. CMU-RI-TR-01-26, Technical Report, The Robotics Institute Carnegie Mellon University Pittsburgh, Pennsylvania, 2001

[60] Korsah, G., Stentz, A., Dias, M.: 'A comprehensive taxonomy for multi-robot task allocation', *Int. J. Robotics Res.*, 2013, **35**, pp. 514–527

[61] Chhetri, A.S.: 'Sensor scheduling and efficient algorithm implementation for target tracking'. PhD dissertation, Arizona State University, 2006

[62] Kalandros, M., Pao, L.Y.: 'Covariance control for multisensor system', *IEEE Trans. Aerosp. Electron. Syst.*, 2002, **38**, (4), pp. 1138–1157

[63] Chhetri, A.S., Morrell, D., Papandreou-Suppappola, A.: 'Nonmyopic sensor scheduling and its efficient implementation for target tracking applications', *EURASIP J. Appl. Signal Process.*, 2006, **2006**, pp. 1–18

[64] Ferri, G., Cococcioni, M., Alvarez, A.: 'Mission planning and decision support for underwater glider networks: A sampling on-demand approach', *Sensors*, 2016, **16**, (1), p. 28. Available at http://www.mdpi.com/1424-8220/16/1/28

[65] Nakamura, Y.: 'Data fusion in robotics and machine intelligence', 1992, ch. Geometric Fusion: Minimizing Uncertainty Volumes, pp. 457–480

[66] Wang, H., Yao, K., Estrin, D.: 'Information-theoretic approaches for sensor selection and placement in sensor networks for target localization and tracking', *J. Commun. Netw.*, 2005, **7**, (4), pp. 438–449

[67] Ryan, A., Durrant-Whyte, H., Hendrick, J.: 'Information-theoretic sensor motion control for distributed estimation'. ASME 2007 Int. Mechanical Engineering Congress and Exposition, 2007, pp. 725–734

[68] MartíNez, S., Bullo, F.: 'Optimal sensor placement and motion coordination for target tracking', *Automatica*, 2006, **42**, (4), pp. 661–668. doi: 10.1016/j.automatica.2005.12.018

[69] Cover, T.M., Thomas, J.A.: '*Elements of information theory (Wiley series in telecommunications and signal processing)*' (Wiley-Interscience, 2006)

[70] Munafò, A., Sliwka, J., Alves, J.: 'Dynamic placement of a constellation of surface buoys for enhanced underwater positioning'. OCEANS 2015, Genova, 18–21 May 2015

[71] Hernandez, M.L., Kirubarajan, T., Bar-Shalom, Y.: 'Multisensor resource deployment using posterior Cramr-Rao bounds', *IEEE Trans. Aerosp. Electron. Syst.*, 2004, **40**, (2), pp. 399–416

[72] Kangsheng, T., Zhu, G.: 'Sensor management based on fisher information gain', *J. Syst. Eng. Electron.*, 2006, **17**, (3), pp. 531–534

[73] Hero, A.O., Castan, D., Cochran, D., *et al.*: '*Foundations and applications of sensor management*' (Springer Publishing Company, Incorporated, 2010, 1st edn.)

[74] Manyika, J.M., Durrant-Whyte, H.F.: 'Information-theoretic approach to management in decentralized data fusion'. Proc. Meeting of Int. Soc. for Optical Engineering (SPIE), 1992, vol. **202**

[75] Schmaedeke, W.W.: 'Information-based sensor management'. Proc. Meeting of Int. Society for Optical Engineering (SPIE), 1993, vol. **156**

[76] Huber, M.: 'Probabilistic framework for sensor management'. PhD dissertation, Universitat Karlsruhe (TH), 2009

[77] Hoffmann, G.M., Tomlin, C.J.: 'Mobile sensor network control using mutual information methods and particle filters', *IEEE Trans. Autom. Control*, 2010, **55**, (1), pp. 32–47

[78] Charrow, B., Liu, S., Kumar, V., *et al.*: 'Information-theoretic mapping using cauchy-schwarz quadratic mutual information'. 2015 IEEE Int. Conf. Robotics and Automation (ICRA), May 2015, pp. 4791–4798

[79] Grocholsky, B.: 'Information-theoretic control of multiple sensor platforms'. PhD dissertation, Australian Centre for Field Robotics, 2002

[80] Kreucher, C., Kastella, K., Hero, A.O.: 'Information based sensor management for multitarget tracking'. Meeting of Int. Society for Optical Engineering (SPIE), San Diego, 2003

[81] Kreucher, C., Kastella, K., Hero, A.O.: 'A Bayesian method for integrated multitarget tracking and sensor management'. Proc. 6th Int. Conf. Information Fusion, Cairns, QLD, Australia, 2003, pp. 132–139

[82] Zhang, G., Ferrari, S., Qian, M.: 'An information roadmap method for robotic sensor path planning', *J. Intell. Robotic Syst.*, 2009, **56**, (1), pp. 69–98

[83] Bullo, F., Cortes, J., Martinez, S.: '*Distributed control of robotic networks: a mathematical approach to motion coordination algorithms*' (Princeton University Press, Princeton, NJ, USA, 2009)

[84] Bertsekas, D.: '*Dynamic programming and optimal control*' (Athena Scientific, 2007)

[85] Page, S.: 'Multiple-objective sensor management and optimisation'. PhD dissertation, University of Southampton, Southampton, UK, 2009

[86] Thrun, S., Burgard, W., Fox, D.: '*Probabilistic robotics*' (The MIT Press, Cambridge, MA, USA, 2005)

[87] Bertsekas, D.: 'Dynamic programming and suboptimal control: a survey from ADP to MPC'. Proc. of the Conf. Decision and Control, 2005

[88] Goldhahn, R., LePage, K., Braca, P., *et al.*: 'Environmentally sensitive AUV behaviors for collaborative multistatic surveillance networks'. Underwater Acoustic Signal Processing Workshop, West Greenwich, RI, USA, 16–18 October 2013

[89] LePage, K., Hamilton, M., Kemna, S.: 'Autonomous underwater vehicles for active multistatic undersea surveillance'. Proc. 4th Int. Conf. Underwater Acoustic Measurements: Technologies and Results, Kos, Greece, June 2011, pp. 1471–1478

[90] Ferri, G., Munafò, A., LePage, K.: 'On data-driven control strategies for AUVs to track targets in sonar surveillance scenarios', *J. Oceanic Eng. (under review)*, 2017, pp. 1–25

[91] Harrison, C.H.: 'Fast bistatic signal-to-reverberation-ratio calculation', *J. Comput. Acoust.*, 2005, **13**, (2), pp. 317–340

[92] Munafò, A., Ferri, G., LePage, K.: 'AUV active perception; exploiting the water column'. OCEANS 2017, Aberdeen, UK, 2017

[93] Armbrust, C., Cubber, G.D., Berns, K.: '*Field and assistive robotics – advances in systems and algorithms*' (Shaker Verlag), ch. ICARUS Control Systems for Search and Rescue Robots, pp. 1–16

[94] Balch, T., Arkin, R.: 'Behavior-based formation control for multi-robot teams', *IEEE Trans. Robot. Autom.*, 1998, **14**, (6), pp. 926–939

[95] Brooks, R.: 'Intelligence without representation', *Artif. Intell.*, 1991, **47**, (13), pp. 139–159

[96] Carreras, M., Batlle, J., Ridan, P., *et al.*: 'An overview on behaviour-based methods for AUV control'. IFAC Conf., 1999, pp. 141–146

[97] Kim, T., Yuh, J.: 'Development of a real-time control architecture for a semi-autonomous underwater vehicle for intervention missions', *Control Eng. Pract.*, 2004, **12**, (12), pp. 1521–1530. Available at http://www.sciencedirect.com/science/article/pii/S0967066103002909

[98] Evans, J., Sotzing, C.C., Patrón, P., *et al.*: 'Cooperative planning architectures for multi-vehicle autonomous operations'. Proc. of the 1st SEAS DTC Technical Conf., 2006

[99] McGann, C., Py, F., Rajan, K., *et al.*: 'A deliberative architecture for AUV control'. ICRA 2008, Pasadena, CA, 2008

[100] Goldberg, D.: 'Huxley: A flexible robot control architecture for autonomous underwater vehicles'. OCEANS 2011 IEEE – Spain, June 2011, pp. 1–10

[101] Benjamin, M.R., Schmidt, H., Newman, P.M., *et al.*: 'Nested autonomy for unmanned marine vehicles with MOOS-IVP', *J. Field Robot.*, 2010, **27**, (6), pp. 834–875. doi: 10.1002/rob.20370

[102] Allotta, B., Caiti, A., Chisci, L., *et al.*: 'An unscented kalman filter based navigation algorithm for autonomous underwater vehicles', *Mechatronics*, 2016, **39**, pp. 185–195

[103] Furfaro, T., Alves, J.: 'An application of distributed long baseline-node ranging in an underwater network'. Underwater Communications and Networking (UComms), 2014, pp. 1–5

[104] Munafò, A., Furfaro, T., Ferri, G., *et al.*: 'Supporting auv localisation through next generation underwater acoustic networks: Results from the field'. 2016 IEEE/RSJ Int. Conf. Intelligent Robots and Systems (IROS), October 2016, pp. 1328–1333

[105] Moreno-Salinas, D., Pascoal, A., Aranda, J.: 'Optimal sensor placement for multiple underwater target localization with acoustic range measurements'. Proc. of IFAC World Conf., 2011

[106] Moreno-Salinas, D., Pascoal, A., Aranda, J.: 'Sensor networks for optimal target localization with bearings-only measurements in constrained three-dimensional scenarios', *Sensors*, 2013, **13**, pp. 10386–10417

[107] Savla, K., Notarstefano, G., Bullo, F.: 'Maintaining limited-range connectivity among second-order agents', *SIAM J. Control Optim*, 2009, **48**, pp. 187–205

[108] Alvarez, A., Mourre, B.: 'Oceanographic field estimates from remote sensing and glider fleets', *J. Atmos. Ocean. Technol.*, 2012, **29**, (11), pp. 1657–1662

[109] Leonard, N.: '*Handbook of ocean engineering*' (Springer Dordrecht Heidelberg London New York, 2016), ch. Cooperative vehicle environmental monitoring, pp. 441–458

[110] Grasso, R., Braca, P., Fortunati, S., *et al.*: 'Dynamic underwater glider network for environmental field estimation', *IEEE Trans. Aerosp. Electron. Syst.*, 2016, **52**, (1), pp. 379–395

[111] Leonard, N., Paley, D., Davis, R., *et al.*: 'Coordinated control of an underwater glider fleet in an adaptive ocean sampling field experiment in Monterey Bay', *J. Field Robot.*, 2010, **27**, (6), pp. 718–740

[112] Paley, D.: 'Cooperative control of collective motion for ocean sampling with autonomous vehicles'. PhD dissertation, Princeton University, 2007

[113] Paley, D., Zhang, F., Leonard, N.: 'Cooperative control for ocean sampling: The glider coordinated control system', *IEEE Trans. Control Syst. Technol.*, 2008, **16**, (4), p. 735744

[114] Caiti, A., Munafò, A., Viviani, R.: 'Adaptive on-line planning of environmental sampling missions with a team of cooperating autonomous underwater vehicles', *Int. J. Control*, 2007, **80**, (7), pp. 1151–1168

[115] Garau, B., Bonet, M., Alvarez, A., *et al.*: 'Path planning for autonomous underwater vehicles in realistic oceanic currents field: application to gliders in the western Mediterranean sea', *J. Marit. Res.*, 2009, **6**, (2), pp. 5–22

[116] Caiti, A., Fabbri, T., Fenucci, D., *et al.*: 'Potential games and AUVs cooperation: First results from the THESAURUS project'. 2013 MTS/IEEE OCEANS – Bergen, June 2013, pp. 1–6

[117] Stentz, A., Dias, B.: 'A free market architecture for coordinating multiple robots'. CMURI-TR-99-42, Technical Report, 1999

[118] Lagoudakis, M., Markakis, E., Kempe, D., *et al.*: 'Auction-based multi-robot routing'. Robotics: Science and Systems, 2005

[119] Stone, P., Veloso, M.: 'Task decomposition and dynamic role assignment for real-time strategic teamwork', *Intelligent Agents V: Agent Theories, Architectures, and Languages: 5h International Workshop, ATAL'98 Paris, France*, 1998, pp. 293–308

[120] Antonelli, G., Arrichiello, F., Chiaverini, S.: 'The null-space-based behavioral control for mobile robots'. IEEE Computational Intelligence in Robotics and Automation (CIRA2005), 2005

[121] Mosteo, A.R., Montano, L.: 'A survey of multi-robot task allocation'. AMI-009-10-TEC, Technical Report, University of Zaragoza, 2010

[122] Gerkey, B., Mataric, M.: 'A formal analysis and taxonomy of task allocation in multirobot systems', *Int. J. Robot. Res.*, 2004, **23**, (9), pp. 939–954

[123] Bertsekas, D.: 'Dynamic programming and suboptimal control: a survey from ADP to MPC', *Eur. J. Control*, 2005, **11**, pp. 310–334

[124] Yan, Z., Jouandeau, N., Cherif, A.: 'A survey and analysis of multi-robot coordination', *Int. J. Adv. Robotic Syst.*, 2013, **10**, pp. 1–18

[125] Werger, B., Mataric, M.: 'Broadcast of local eligibility: behavior-based control for strongly cooperative robot teams'. 4th Int. Conf. Autonomous Agents (AGENTS 2000), 2000

[126] Parker, L.E.: 'ALLIANCE: an architecture for fault-tolerant multi-robot cooperation', *IEEE Trans. Robot. Autom.*, 1998, **14**, (2), pp. 220–240

[127] Agassounon, W., Martinoli, A.: 'Efficiency and robustness of threshold-based distributed allocation algorithms in multi-agent systems'. Proc. of the Int. Joint Conf. Autonomous Agents and Multiagent Systems, 2002

[128] Krieger, M., Billeter, J.: 'The call of duty: self-organized task allocation in a population of up to twelve mobile robots', *Robot. Auton. Syst.*, 2000, **30**, pp. 1–2

[129] Porta, J., Spaan, M., Vlassis, N.: 'Robot planning in partially observable continuous domains'. Robotics: Science and Systems, 2005

[130] Viguria, A.: 'Market-based distributed task allocation methodologies applied to multi-robot exploration'. PhD dissertation, University of Seville, 2009

[131] Tsiogkas, N., Papadimitriou, G., Saigol, Z., *et al.*: 'Efficient multi-AUV cooperation using semantic knowledge representation for underwater archaeology missions'. Oceans – St. John's 2014, 2014

[132] Deng, Y., Beaujean, P., An, E., *et al.*: 'Task allocation and path planning for collaborative AUVs operating through an underwater acoustic network'. OCEANS 2010, 2010

[133] Kulkarni, I., Pompili, D.: 'Task allocation for networked autonomous underwater vehicles in critical missions', *IEEE J. Sel. Areas Commun.*, 2010, **28**, p. 5

[134] Ferri, G., Munafò, A., Tesei, A., *et al.*: 'A market-based task allocation framework for autonomous underwater surveillance networks'. OCEANS 2017, Aberdeen, UK (under review), 2017

[135] Nielsen, R.: '*Sonar signal processing*' (Artech House, Inc., 1991)

[136] Van Trees, H.: '*Detection, estimation, and modulation theory*' (John Wiley & Sons, 2004)

[137] Stewart, J.-M., Jiang, M., Marra, M.: 'A neural network approach to classification of sidescan sonar imagery from a midocean ridge area', *IEEE J. Ocean. Eng.*, 1994, **19**, (2), pp. 214–224

[138] Streilein, W.W., Gaudiano, P., Carpenter, G.A.: 'A neural network for object recognition through sonar on a mobile robot'. Intelligent Control (ISIC), 1998. Held jointly with IEEE Int. Symp. on Computational Intelligence in Robotics and Automation (CIRA), Intelligent Systems and Semiotics (ISAS), Proc. IEEE, 1998, pp. 271–276

[139] Williams, D., Fakiris, E.: 'Exploiting environmental information for improved underwater target classification in sonar imagery', *IEEE Trans. Geosci. Remote Sens.*, 2014, **52**, (10), pp. 6284–6297

[140] Myers, V., Williams, D.: 'Adaptive multiview target classification in synthetic aperture sonar images using a partially observable Markov decision process', *IEEE J. Ocean. Eng.*, 2012, **37**, (1), pp. 45–55

[141] Williams, D.-P., Myers, V., Silvious, M.S.: 'Mine classification with imbalanced data', *IEEE Geosci. Remote Sens. Lett.*, 2009, **6**, (3), pp. 528–532

[142] Bittle, M., Duncan, A.: 'A review of current marine mammal detection and classification algorithms for use in automated passive acoustic monitoring'. Proc. Acoustics, 2013, vol. **2013**

[143] Kang, C., Zhang, X., Zhang, A., Lin, H.: 'Underwater acoustic targets classification using welch spectrum estimation and neural networks'. Advances in Neural Networks-ISNN 2004, 2004, pp. 930–935

[144] Tesei, A., Been, R., Williams, D.*, et al.*: 'Passive acoustic surveillance of surface vessels using tridimensional array on an underwater glider'. OCEANS 2015 – Genova, May 2015, pp. 1–8

[145] Murphy, P., Hines, S.M., Dunphy, K.: 'Classifying continuous active sonar echoes for target recognition'. Proc. 2nd Int. Conf. and Exhibition on Underwater Acoustics, 2014, pp. 811–818

[146] Sildam, J., Ehlers, F.: 'Supervised track classification in support of AUV decision making'. Proc. UAM 2011, 2011

[147] Canepa, G., Munafò, A., Micheli, M.*, et al.*: 'Real-time continuous active sonar processing'. IEEE/MTS OCEANS 2015 – Genova, 2015, pp. 1–6

[148] Jensen, F.B., Kuperman, W.A., Porter, M.B.*, et al.*: '*Computational ocean acoustics*' (Springer, New York, NY, USA, 2011)

[149] Kuperman, W., Ingenito, F.: 'Attenuation of the coherent component of sound propagating in shallow water with rough boundaries', *J. Acoust. Soc. Am.*, 1977, **61**, (5), pp. 1178–1187

[150] Dahl, P.: 'High-frequency forward scattering from the sea surface: the characteristic scales of time and angle spreading', *IEEE J. Oceanic Eng.*, 2002, **26**, (1), pp. 141–151

[151] Siderius, M., Porter, M.B.: 'Modeling broadband ocean acoustic transmissions with time-varying sea surfaces', *J. Acoust. Soc. Am.*, 2008, **124**, (1), pp. 137–150

[152] Wenz, G.: 'Acoustic ambient noise in the ocean: spectra and sources', *J. Acoust. Soc. Am.*, 1962, **34**, (12), pp. 1936–1956

[153] Costas, J.: 'Medium constraints on sonar design and performance', *IEEE Trans. Aerosp. Electron. Syst.*, 1975, **11**, (5), pp. 973–973.

[154] Knight, W.C., Pridham, R.G., Kay, S.M.: 'Digital signal processing for sonar', *Proc. IEEE*, 1981, **69**, (11), pp. 1451–1506

[155] Catipovic, J.: 'Performance limitations in underwater acoustic telemetry', *IEEE J. Ocean. Eng.*, 1990, **15**, (3), pp. 205–216

[156] Abraham, D., Lyons, A.: 'Reverberation envelope statistics and their dependence on sonar bandwidth and scattering patch size', *IEEE J. Ocean. Eng.*, 2004, **29**, (1), pp. 126–137

[157] Abraham, D.A., Willett, P.K.: 'Active sonar detection in shallow water using the page test', *IEEE J. Ocean. Eng.*, 2002, **27**, (1), pp. 35–46

[158] Kincaid, T.: 'Optimum waveforms for correlation detection in the sonar environment: noiselimited conditions', *J. Acoust. Soc. Am.*, 1968, **43**, (2), pp. 258–268

[159] Haykin, S.: 'Cognitive radar: a way of the future', *IEEE Signal Process. Mag.*, 2006, **23**, (1), pp. 30–40

[160] Sharaga, N., Tabrikian, J.: 'Optimal adaptive transmit beamforming for cognitive MIMO sonar in a shallow water waveguide'. 22nd European Signal Processing Conf. (EUSIPCO), 2014, vol. **145**, pp. 1960–1964

[161] Haralabus, G., Baldacci, A.: 'Unambiguous triplet array beamforming and calibration algorithms to facilitate an environmentally adaptive active sonar concept'. IEEE OCEANS Conf., January 2006, vol. **23**, (1), pp. 30–40

[162] Claussen, T., Nguyen, V.: 'Real-time cognitive sonar system with target-optimized adaptive signal processing through multi-layer data fusion'. IEEE Int. Conf. Multisensor Fusion and Integration for Intelligent Systems (MFI), September 2006

[163] Baldacci, A., Haralabus, G.: 'Signal processing for an active sonar system suitable for advanced sensor technology applications and environmental adaptation schemes'. 14th European Signal Processing Conf., 2006, pp. 1–5

[164] Li, W., Chen, G., Blasch, E.*, et al.*: 'Cognitive MIMO sonar based robust target detection for harbor and maritime surveillance applications'. IEEE Aerospace Conf., March 2009, vol. **54**, (3), pp. 1–9

[165] Krim, H., Viberg, M.: 'Two decades of array signal processing research: the parametric approach', *IEEE Signal Process. Mag.*, 1996, **13**, (4), pp. 67–94

[166] Le Chevalier, F., Montecot, M., Doisy, Y.*, et al.*: 'STAP developments in Thales'. Radar Conf., 2009. EuRAD 2009. European, 2009, pp. 53–56

[167] van Ijsselmuide, S., Deruaz, L., Been, R.*, et al.*: 'Sonar waveforms for reverberation rejection, part IV: adaptive processing'. UDT Europe-Conf. Proc. Undersea Defence Technology, La Spezia, Italy, 18–21 June 2002

[168] Kim, K.M., Lee, C., Youn, D.H.: 'Adaptive processing technique for enhanced CFAR detecting performance in active sonar systems', *IEEE Trans. Aerosp. Electron. Syst.*, 2000, **36**, (2), pp. 693–700

[169] Mio, K., Chocheyras, Y., Doisy, Y.: 'Space time adaptive processing for low frequency sonar'. OCEANS 2000 MTS/IEEE Conf. and Exhibition, 2000, vol. **2**, pp. 1315–1319

[170] Klemm, R.: 'Comparison between monostatic and bistatic antenna configurations for STAP', *IEEE Trans. Aerosp. Electron. Syst.*, 2000, **36**, (2), pp. 596–608

[171] Klemm, R.: '*Principles of space-time adaptive processing*' (IET, 2002), no. 159

[172] Zimmerman, M., Coolidge, M., Lapisky, E.: '3-D sonar system'. US Patent App. 11/581,626, October 2006

[173] Hamilton, M.J., Kemna, S., Hughes, D.: 'Antisubmarine warfare applications for autonomous underwater vehicles: the GLINT09 sea trial results', *J. Field Robot.*, 2010, **27**, (6), pp. 890–902

[174] Cox, H.: 'Fundamentals of bistatic active sonar', in '*Underwater acoustic data processing*' (Springer, 1989), pp. 3–24

[175] Mozzone, L., Bongi, S., Filocca, F.: 'Diversity in multistatic active sonar'. MTS/IEEE OCEANS'99. IEEE, 1999, vol. **2**, pp. 1058–1063

[176] Fishler, E., Haimovich, A., Blum, R.S.*, et al.*: 'Spatial diversity in radars-models and detection performance', *IEEE Trans. Signal Process.*, 2006, **54**, (3), pp. 823–838

[177] Grimmett, D.J., Sullivan, S., Alsup, J.: 'Modeling specular occurrence in distributed multistatic fields'. OCEANS 2008-MTS/IEEE Kobe Techno-Ocean, 2008, pp. 1–8

[178] Preston, J.R., Abraham, D.A.: 'Statistical analysis of multistatic echoes from a shipwreck in the Malta Plateau', *IEEE J. Ocean. Eng.*, 2015, **40**, (3), pp. 643–656

[179] Grimmett, D.: 'Automatic identification of specular detections in multistatic sonar systems'. OCEANS 2009, 2009, pp. 1–10

[180] Gianelli, C., Xu, L., Li, J.: 'Active sonar systems in the presence of strong direct blast'. OCEANS 2015 – Genova, May 2015, pp. 1–10

[181] Jauffret, C., Perez, A.-C., Blanc-Benon, P.*, et al.*: 'Doppler-only target motion analysis in a high duty cycle sonar system'. Proc. 19th Int. Conf. Information Fusion – Heidelberg, 2016

[182] Haykin, S., Xue, Y., Davidson, T.N.: 'Optimal waveform design for cognitive radar'. 2008 42nd Asilomar Conf. Signals, Systems and Computers, 2008, pp. 3–7

[183] Collins, T., Atkins, P.: 'Doppler-sensitive active sonar pulse designs for reverberation processing', *IEE Proc. Radar Sonar Navig.*, 1998, **145**, (6), pp. 347–353

[184] Kershaw, D.J., Evans, R.J.: 'Optimal waveform selection for tracking systems', *IEEE Trans. Inf. Theory*, 1994, **40**, (5), pp. 1536–1550

[185] Doisy, Y., Deruaz, L., van IJsselmuide, S.P.*, et al.*: 'Reverberation suppression using wideband Doppler-sensitive pulses', *IEEE J. Ocean. Eng.*, 2008, **33**, (4), pp. 419–433

[186] Doisy, Y., Deruaz, L., Beerens, S.P.*, et al.*: 'Target Doppler estimation using wideband frequency modulated signals', *IEEE Trans. Signal Process.*, 2000, **48**, (5), pp. 1213–1224

[187] Doisy, Y., Le Chevalier, F.: 'Airborne radar and shipborne sonar: recent advances and compared solutions'. 2009 Int. Radar Conf. Surveillance for a Safer World (RADAR 2009), 2009, pp. 1–6

[188] Hines, P.C., Hicks, K., Murphy, S.M.*, et al.*: 'Measurements of signal coherence for high and low duty cycle sonars in a shallow water channel'. IEEE/MTS OCEANS 2015 - Genova, 2015, pp. 1–5

[189] Hines, P.C., Murphy, S.M., Abraham, D.A.*, et al.*: 'The dependence of signal coherence on sea-surface roughness for high and low duty cycle sonars in a shallow-water channel', *IEEE J. Ocean. Eng.*, 2016, **42**, (2), pp. 298–318

[190] Plate, R., Grimmett, D.: 'High duty cycle (HDC) sonar processing interval and bandwidth effects for the TREX'13 dataset'. IEEE/MTS OCEANS 2015 - Genova, 2015, pp. 1–10

[191] Grimmett, D., Plate, R.: 'Temporal and Doppler coherence limits for the underwater acoustic channel during the LCAS'15 high duty cycle sonar experiment'. OCEANS 2016 MTS/IEEE Monterey, 2016

[192] Murphy, S., Hines, P.: 'Sub-band processing of continuous active sonar signals in shallow water'. OCEANS 2015 - Genova, 2015

[193] Murphy, S.M., Coffin, M., Hines, P.C.*, et al.*: 'Testing the feasibility of a concurrent comparison of continuous and pulsed active sonar', *J. Acoust. Soc. Am.*, 2016, **140**, (4), pp. 3285–3285

[194] Abraham, D.A., Hines, P.C.: 'Effect of pulse duration on echo matched-filter statistics in a shallow-water channel', *IEEE J. Ocean. Eng.*, 2016, **42**, (2), pp. 319–334

[195] Murphy, S.M., Scrutton, J.G.E., Hines, P.C.: 'Experimental implementation of an echo repeater for continuous active sonar', *IEEE J. Ocean. Eng.*, 2016, **42**, (2), pp. 289–297

[196] Pailhas, Y., Petillot, Y.: 'Neither PAS nor CAS: MIMO'. IEEE OCEANS 2016 - Shanghai, 2016, pp. 1–4

[197] Tesei, A., Fioravanti, S., Grandi, V.*, et al.*: 'Localization of small surface vessels through acoustic data fusion of two tetrahedral arrays of hydrophones'. Proc. of Meetings on Acoustics, 2012, vol. **17**

[198] Soares, C., Jesus, S., Hursky, P.*, et al.*: 'Random array of drifting acoustic receivers (RADAR'07)'. CINTAL – SiPLAB, Technical Report Rep 04/07, December 2007

[199] André, M.: 'Ocean noise: composing soundscapes from real-time acoustic data streams', *Introducing Noise into the Marine Environment – What Are the Requirements for an Impact Assessment*, 2014, **6**, p. 95

[200] Glegg, S.A., Olivieri, M.P., Coulson, R.K.*, et al.*: 'A passive sonar system based on an autonomous underwater vehicle', *IEEE J. Ocean. Eng.*, 2001, **26**, (4), pp. 700–710

[201] Gebbie, P.N.J., Siderius, M., Miller, J.: 'Passive localization of noise-producing targets using a compact volumetric array', *J. Acoust. Soc. Am.*, 2014, **136**, (1), pp. 80–89

[202] Tesei, A., Been, R., Troiano, L.*, et al.*: 'Small vessel detection through the use of an underwater glider'. Proc. 2nd Int. Conf. Underwater Acoustics, 2014

[203] Gebbie, J., Siderius, M., Nielsen, P.*, et al.*: 'Small boat localization using adaptive three-dimensional beamforming on a tetrahedral and vertical line array'. Proc. Meetings on Acoustics, 2013, vol. **19**

[204] Hassad, J., Boucher, R.: 'Optimum estimation of time delay by a generalized correlator', *IEEE Trans. Acoust. Speech Signal Process.*, 1979, **27**, (4), pp. 373–380

[205] Watkins, W., Schevill, W.: 'Four hydrophone array for acoustic threedimensional location'. Technical Report Rep 71-60, Woods Hole Oceanographic Institute, October 1971

[206] Abdi, H.: 'The method of least squares', '*Encyclopedia of measurement and statistics*' (Thousand Oaks, CA, USA, 2007)

[207] Meyer, F., Braca, P., Willett, P.*, et al.*: 'A scalable algorithm for tracking an unknown number of targets using multiple sensors', *IEEE Trans. Signal Process.*, 2017, **65**, pp. 3478–3493. Available at http://arxiv.org/abs/1607.07647v1

[208] Lo, K., Ferguson, B., Gao, Y.*, et al.*: 'Dynamic Cramér-Rao bound for target tracking in clutter', *IEEE Trans. Aerosp. Electron. Syst.*, 2003, **39**, (1), pp. 259–268

[209] Mallick, M., Vo, B.N., Kirubarajan, T.*, et al.*: 'Introduction to the issue on multitarget tracking', *IEEE J. Sel. Topics Signal Process.*, 2013, **7**, (3), pp. 373–375

[210] Uhlmann, J.: 'Algorithms for multiple-target tracking', *Am. Sci.*, 1992, **80**, (2), pp. 128–141

[211] Rasmussen, C., Hager, G.D.: 'Probabilistic data association methods for tracking complex visual objects', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2001, **23**, (6), pp. 560–576

[212] Adrian, R.J.: 'Particle-imaging techniques for experimental fluid mechanics', *Annu. Rev. Fluid Mech.*, 1991, **23**, (1), pp. 261–304

[213] Genovesio, A., Liedl, T., Emiliani, V., *et al.*: 'Multiple particle tracking in 3-D +t microscopy: method and application to the tracking of endocytosed quantum dots', *IEEE Trans. Image Process.*, 2006, **15**, (5), pp. 1062–1070

[214] Mullane, J., Vo, B.-N., Adams, M., *et al.*: '*Random finite sets for robot mapping and SLAM – new concepts in autonomous robotic map representations*' (Springer, 2011), vol. **72**, ser. Springer Tracts in Advanced Robotics

[215] Witrisal, K., Meissner, P., Leitinger, E., *et al.*: 'High-accuracy localization for assisted living: 5G systems will turn multipath channels from foe to friend', *IEEE Signal Process. Mag.*, 2016, **33**, (2), pp. 59–70

[216] Leitinger, E., Meyer, F., Meissner, P., *et al.*: 'Belief propagation based joint probabilistic data association for multipath-assisted indoor navigation and tracking'. Proc. IEEE ICL-GNSS-16, Barcelona, Spain, June 2016

[217] Urmson, C., Anhalt, J., Bagnell, D., *et al.*: 'Autonomous driving in urban environments: boss and the urban challenge', *J. Field Robot.*, 2008, **25**, (8), pp. 425–466

[218] Levinson, J., Askeland, J., Becker, J., *et al.*: 'Towards fully autonomous driving: systems and algorithms'. Proc. IEEE IV 2011, Baden-Baden, Germany, June 2011, pp. 163–168

[219] Reuter, S., Dietmayer, K.: 'Pedestrian tracking using random finite sets'. Proc. FUSION-11, Chicago, IL, USA, July 2011

[220] Fortmann, T., Bar-Shalom, Y., Scheffe, M.: 'Sonar tracking of multiple targets using joint probabilistic data association', *IEEE J. Ocean. Eng.*, 1983, **8**, (3), pp. 173–184

[221] Bar-Shalom, Y., Willett, P.K., Tian, X.: '*Tracking and data fusion: a handbook of algorithms*' (Yaakov Bar-Shalom, Storrs, CT, USA, 2011)

[222] Sittler, R.W.: 'An optimal data association problem in surveillance theory', *IEEE Trans. Military Electron.*, 1964, **8**, (2), pp. 125–139

[223] Bar-Shalom, Y.: 'Tracking methods in a multitarget environment', *IEEE Trans. Autom. Control*, 1978, **23**, (4), pp. 618–626

[224] Bar-Shalom, Y., Tse, E.: 'Tracking in a cluttered environment with probabilistic data association', *Automatica*, 1975, **11**, (5), pp. 451–460

[225] Singer, R., Sea, R., Housewright, K.: 'Derivation and evaluation of improved tracking filter for use in dense multitarget environments', *IEEE Trans. Inf. Theory*, 1974, **20**, (4), pp. 423–432

[226] Reid, D.B.: 'An algorithm for tracking multiple targets', *IEEE Trans. Autom. Control*, 1979, **24**, (6), pp. 843–854

[227] Kirubarajan, T., Bar-Shalom, Y.: 'Probabilistic data association techniques for target tracking in clutter', *Proc. IEEE*, 2004, **92**, (3), pp. 536–557

[228] Blackman, S.S.: 'Multiple hypothesis tracking for multiple target tracking', *IEEE Trans. Aerosp. Electron. Syst.*, 2004, **19**, pp. 5–18

[229] Mazor, E., Averbuch, A., Bar-Shalom, Y., *et al.*: 'Interacting multiple model methods in target tracking: A survey', *IEEE Trans. Aerosp. Electron. Syst.*, 1998, **34**, (1), pp. 103–123

[230] Kirubarajan, T., Barshalom, Y., Pattipati, K., *et al.*: 'Ground target tracking with variable structure IMM estimator', *IEEE Trans. Aerosp. Electron. Syst.*, 2000, **36**, (1), pp. 26–46

[231] Chang, K.-C., Bar-Shalom, Y.: 'Joint probabilistic data association for multitarget tracking with possibly unresolved measurements and maneuvers', *IEEE Trans. Autom. Control*, 1984, **29**, (7), pp. 585–594

[232] Koch, J.W.: 'Bayesian approach to extended object and cluster tracking using random matrices', *IEEE Trans. Aerosp. Electron. Syst.*, 2008, **44**, (3), pp. 1042–1059

[233] Pulford, G.W.: 'Taxonomy of multiple target tracking methods', *Proc. IEE Radar Sonar Navig.*, 2005, **152**, (5), pp. 291–304

[234] Bar-Shalom, Y., Li, X.-R.: '*Multitarget-multisensor tracking: principles and techniques*' (Yaakov Bar-Shalom, Storrs, CT, USA, 1995)

[235] Mahler, R.P.S.: 'Multitarget Bayes filtering via first-order multitarget moments', *IEEE Trans. Aerosp. Electron. Syst.*, 2003, **39**, (4), pp. 1152–1178

[236] Vo, B.-N., Singh, S., Doucet, A.: 'Sequential Monte Carlo methods for multitarget filtering with random finite sets', *IEEE Trans. Aerosp. Electron. Syst.*, 2005, **41**, (4), pp. 1224–1245

[237] Mahler, R.: '*Statistical multisource-multitarget information fusion*' (Artech House, Norwood, MA, USA, 2007)

[238] Braca, P., Marano, S., Matta, V., *et al.*: 'Asymptotic efficiency of the PHD in multitarget/multisensor estimation', *IEEE J. Sel. Topics Signal Process.*, 2013, **7**, (3), pp. 553–564

[239] Vo, B.-T., Vo, B.-N., Cantoni, A.: 'Analytic implementations of the cardinalized probability hypothesis density filter', *IEEE Trans. Signal Process.*, 2007, **55**, (7), pp. 3553–3567

[240] Vo, B.-T., Vo, B.-N., Cantoni, A.: 'The cardinality balanced multi-target multi-Bernoulli filter and its implementations', *IEEE Trans. Signal Process.*, 2009, **57**, (2), pp. 409–423

[241] Vo, B.-T., Vo, B.-N.: 'Labeled random finite sets and multi-object conjugate priors', *IEEE Trans. Signal Process.*, 2013, **61**, (13), pp. 3460–3475

[242] Vo, B.-N., Vo, B.-T., Phung, D.: 'Labeled random finite sets and the Bayes multi-target tracking filter', *IEEE Trans. Signal Process.*, 2014, **62**, (24), pp. 6554–6567

[243] Cappe, O., Godsill, S., Moulines, E.: 'An overview of existing methods and recent advances in sequential Monte Carlo', *Proc. IEEE*, 2007, **95**, (5), pp. 899–924

[244] Morelande, M.R., Kreucher, C.M., Kastella, K.: 'A Bayesian approach to multiple target detection and tracking', *IEEE Trans. Signal Process.*, 2007, **55**, (5), pp. 1589–1604

[245] Kschischang, F.R., Frey, B.J., Loeliger, H.-A.: 'Factor graphs and the sum-product algorithm', *IEEE Trans. Inf. Theory*, 2001, **47**, (2), pp. 498–519

[246] Yedidia, J., Freeman, W.T., Weiss, Y.: 'Constructing free-energy approximations and generalized belief propagation algorithms', *IEEE Trans. Inf. Theory*, 2005, **51**, (7), pp. 2282–2312

[247] Horridge, P., Maskell, S.: 'Real-time tracking of hundreds of targets with efficient exact JPDAF implementation'. Proc. FUSION-06, Florence, Italy, July 2006

[248] Chen, Z., Chen, L., Cetin, M., *et al.*: 'An efficient message passing algorithm for multi-target tracking'. Proc. FUSION-09, Seattle, WA, USA, July 2009, pp. 826–833

[249] Williams, J.L., Lau, R.: 'Approximate evaluation of marginal association probabilities with belief propagation', *IEEE Trans. Aerosp. Electron. Syst.*, 2014, **50**, (4), pp. 2942–2959

[250] Williams, J.L.: 'Marginal multi-Bernoulli filters: RFS derivation of MHT, JIPDA and association-based MeMBer', *IEEE Trans. Aerosp. Electron. Syst.*, 2015, **51**, (3), pp. 1664–1687

[251] Meyer, F., Braca, P., Willett, P., *et al.*: 'Scalable multitarget tracking using multiple sensors: a belief propagation approach'. Proc. FUSION-15, Washington, DC, USA, July 2015, pp. 1778–1785

[252] Meyer, F., Braca, P., Willett, P., *et al.*: 'Tracking an unknown number of targets using multiple sensors: a belief propagation method'. Proc. FUSION-16, Heidelberg, Germany, July 2016

[253] Coraluppi, S., Grimmett, D., Theije, P.D.: 'Benchmark evaluation of multistatic trackers'. Proc. FUSION-06, Florence, Italy, July 2006

[254] Braca, P., Goldhahn, R., LePage, K., *et al.*: 'Cognitive multistatic AUV networks'. Proc. FUSION-14, Salamanca, Spain, July 2014

[255] Kay, S.M.: '*Fundamentals of statistical signal processing: estimation theory*' (Prentice-Hall, Upper Saddle River, NJ, USA, 1993)

[256] Braca, P., Willett, P., LePage, K., *et al.*: 'Bayesian tracking in underwater wireless sensor networks with port-starboard ambiguity', *IEEE Trans. Signal Process.*, 2014, **62**, (7), pp. 1864–1878

[257] Schuhmacher, D., Vo, B.-T., Vo, B.-N.: 'A consistent metric for performance evaluation of multi-object filters', *IEEE Trans. Signal Process.*, 2008, **56**, (8), pp. 3447–3457

[258] Braca, P., Goldhahn, R., Ferri, G., *et al.*: 'Distributed information fusion in multistatic sensor networks for underwater surveillance', *IEEE Sens. J.*, 2016, **16**, (11), pp. 4003–4014

[259] Papa, G., Braca, P., Horn, S., *et al.*: 'Multisensor adaptive bayesian tracking under time-varying target detection probability', *IEEE Trans. Aerosp. Electron. Syst.*, 2016, **52**, (5), pp. 2193–2209

[260] Meyer, F., Braca, P., Hlawatsch, F., *et al.*: 'Scalable adaptive multitarget tracking using multiple sensors'. Proc. GLOBECOM, Washington, DC, December 2016

[261] Coraluppi, S., Carthel, C.: 'Distributed tracking in multistatic sonar', *IEEE Trans. Aerosp. Electron. Syst.*, 2005, **41**, (3), pp. 1138–1147

[262] Coraluppi, S.: 'Multistatic sonar localization', *IEEE J. Ocean. Eng.*, 2006, **31**, (4), pp. 964–974

[263] Kar, S., Tandon, R., Poor, H.V., *et al.*: 'Distributed detection in noisy sensor networks'. Proc. ISIT–11, Saint Petersburg, Russia, July 2011, pp. 2856–2860

[264] Bajovic, D., Jakovetic, D., Xavier, J., *et al.*: 'Distributed detection via Gaussian running consensus: large deviations asymptotic analysis', *IEEE Trans. Signal Process.*, 2011, **59**, (9), pp. 4381–4396

[265] Braca, P., Marano, S., Matta, V.: 'Single-transmission distributed detection via order statistics', *IEEE Trans. Signal Process.*, 2012, **60**, (4), pp. 2042–2048

[266] Viswanathan, R., Varshney, P.: 'Distributed detection with multiple sensors Part–I. Fundamentals', *Proc. IEEE*, 1997, **85**, (1), pp. 54–63

[267] Blum, R., Kassam, S., Poor, V.: 'Distributed detection with multiple sensors Part–II. Advanced topics', *Proc. IEEE*, 1997, **85**, (1), pp. 64–79

[268] Boyd, S., Ghosh, A., Prabhakar, B., *et al.*: 'Randomized gossip algorithms', *IEEE Trans. Inf. Theory*, 2006, **52**, (6), pp. 2508–2530

[269] Braca, P., Marano, S., Matta, V., *et al.*: 'Asymptotic optimality of running consensus in testing statistical hypotheses', *IEEE Trans. Signal Process.*, 2010, **58**, (2), pp. 814–825

[270] Braca, P., Marano, S., Matta, V.: 'Enforcing consensus while monitoring the environment in wireless sensor networks', *IEEE Trans. Signal Process.*, 2008, **56**, (7), pp. 3375–3380

[271] Bajovic, D., Jakovetic, D., Moura, J.M.F., *et al.*: 'Large deviations performance of consensus+innovations distributed detection with non-Gaussian observations', *IEEE Trans. Signal Process.*, 2012, **60**, (11), pp. 5987–6002

[272] Cattivelli, F., Sayed, A.: 'Distributed detection over adaptive networks using diffusion adaptation', *IEEE Trans. Signal Process.*, 2011, **59**, (5), pp. 1917–1932

[273] Matta, V., Braca, P., Marano, S., *et al.*: 'Diffusion-based adaptive distributed detection: steady-state performance in the slow adaptation regime', *IEEE Trans. Inf. Theory*, 2016, **62**, (8), pp. 4710–4732

[274] Matta, V., Braca, P., Marano, S., *et al.*: 'Distributed detection over adaptive networks: refined asymptotics and the role of connectivity', *IEEE Trans. Signal Inf. Process. Netw.*, 2016, **2**, (4), pp. 442–460

[275] Olfati-Saber, R.: 'Distributed Kalman filtering for sensor networks'. Proc IEEE CDC-07, New Orleans, LA, USA, December 2007, pp. 5492–5498

[276] Hlinka, O., Sluciak, O., Hlawatsch, F., *et al.*: 'Likelihood consensus and its application to distributed particle filtering', *IEEE Trans. Signal Process.*, 2012, **60**, (8), pp. 4334–4349

[277] Hlinka, O., Hlawatsch, F., Djuric, P.: 'Distributed particle filtering in agent networks: a survey, classification, and comparison', *IEEE Signal Process. Mag.*, 2013, **30**, (1), pp. 61–81

[278] Sandell, N.F., Olfati-Saber, R.: 'Distributed data association for multi-target tracking in sensor networks'. Proc IEEE CDC-08, Cancun, Mexico, December 2008, pp. 1085–1090

[279] Battistelli, G., Chisci, L., Fantacci, C., *et al.*: 'Consensus CPHD filter for distributed multitarget tracking', *IEEE J. Sel. Topics Signal Process.*, 2013, **7**, (3), pp. 508–520

[280] Pelekanakis, K., Baggeroer, A.B.: 'Exploiting space-time-frequency diversity with mimo-ofdm for underwater acoustic communications', *IEEE J. Ocean. Eng.*, 2011, **36**, (4), pp. 502–513
[281] Sendra, S., Lloret, J., Jimenez, J.M., *et al.*: 'Underwater acoustic modems', *IEEE Sens. J.*, 2016, **16**, (11), pp. 4063–4071
[282] Chitre, M., Freitag, L., Sozer, E., *et al.*: 'An architecture for underwater networks'. Proc. of MTS/IEEE OCEANS 2006, Singapore, 16–19 May 2006
[283] Potter, J.R., Alves, J., Furfaro, T., *et al.*: 'Software defined open architecture modem development at CMRE'. Proc. of the 2nd IEEE OES Int. Conf. on Underwater Communications and Networking, ser. UComms'14, Sestri Levante, Italy, 3–5 September 2014
[284] Petrioli, C., Petroccia, R., Potter, J.R., *et al.*: 'The SUNSET framework for simulation, emulation and at-sea testing of underwater wireless sensor networks', *Ad Hoc Netw.*, 2015, **34**, pp. 224–238
[285] Smerdon, A., Bustamante, F., Baker, M.: 'The swigacoustic standard: an acoustic communication standard for the offshore energy community'. 2016 IEEE Third Underwater Communications and Networking Conf. (UComms), August 2016, pp. 1–4
[286] NATO, STANAG 4748 Ed. A ver. 1: 'Digital underwater signalling standard for network node discovery & interoperability', https://nso.nato.int/nso/zPublic/ap/PROM/ANEP-87%20EDA%20V1%20E.pdf, accessed April 2017
[287] Petroccia, R., Alves, J., Zappa, G.: 'Fostering the use of JANUS in operationally-relevant underwater applications'. Proc. 3rd IEEE OES Int. Conf. on Underwater Communications and Networking, ser. UComms16, Lerici, Italy, 30 August–1 September 2016
[288] Alves, J., Furfaro, T., LePage, K., *et al.*: 'Moving janus forward: a look into the future of underwater communications interoperability'. Proc. MTS/IEEE OCEANS 2016, Monterey, CA, USA, 19–23 September 2016
[289] Kilfoyle, D.B., Baggeroer, A.B.: 'The state of the art in underwater acoustic telemetry', *IEEE J. Ocean. Eng.*, 2000, **25**, (1), pp. 4–27
[290] Melodia, T., Khulandjian, H., Kuo, L.-C., *et al.*: 'Advances in underwater acoustic networking', in Basagni, S., Conti, M., Giordano, S., Stojmenovic, I. (Eds.): '*Mobile ad hoc networking: cutting edge directions*' (John Wiley & Sons, Inc., Hoboken, NJ, 2013), ch. 23, pp. 804–852
[291] Chitre, M., Shahabudeen, S., Stojanovic, M.: 'Underwater acoustic communications and networking: recent advances and future challenges', *Mar. Technol. Soc. J.*, 2008, **42**, (1), pp. 103–116
[292] Chen, K., Ma, M., Cheng, E., *et al.*: 'A survey on mac protocols for underwater wireless sensor networks', *IEEE Commun. Surv. Tutor.*, 2014, **16**, (3), pp. 1433–1447
[293] Petrioli, C., Petroccia, R., Potter, J.: 'Performance evaluation of underwater mac protocols: From simulation to at-sea testing'. Proc. IEEE/OES OCEANS 2011, Santander, Spain, 6–9 June 2011
[294] Di Valerio, V., Lo Presti, F., Petrioli, C., *et al.*: 'A self-adaptive protocol stack for underwater wireless sensor networks'. Proc. MTS/IEEE OCEANS 2016, Shanghai, China, 10–13 April 2016, pp. 1–8
[295] Li, N., Martínez, J.-F., Meneses Chaus, J.M., *et al.*: 'A survey on underwater acoustic sensor network routing protocols', *Sensors*, 2016, **16**, (3), p. 414
[296] Alves, J., Petroccia, R., Potter, J.R.: 'MPR: multi-point relay protocol for underwater acoustic networks'. Proc. 9th ACM Int. Conf. on Underwater Networks and Systems, ser. WUWNet'14, Rome, Italy, 12–14 November 2014
[297] Jurdak, R., Ruzzelli, A.G., O'Hare, G.M.P.: 'Design considerations for deploying underwater sensor networks'. Proc. of SensorComm 2007, 14–20 October 2007, pp. 227–232
[298] Basagni, S., Petrioli, C., Petroccia, R., *et al.*: 'CARP: a channel-aware routing protocol for underwater acoustic wireless networks', *Ad Hoc Netw.*, 2015, **34**, pp. 92–104
[299] Braga, J., Martins, R., Petrioli, C., *et al.*: 'Cooperation and networking in an underwater network composed by heterogeneous assets'. Proc. of MTS/IEEE OCEANS 2016, Monterey, CA, USA, 19–23 September 2016, pp. 1–9
[300] Fall, K.: 'A delay-tolerant network architecture for challenged internets'. Proc. 2003 Conf. on Applications, Technologies, Architectures, and Protocols for Computer Communications, ser. SIGCOMM'03, 25–29 August 2003, pp. 27–34
[301] Merani, D., Berni, A., Potter, J., *et al.*: 'An underwater convergence layer for disruption tolerant networking'. 2011 Baltic Congress on Future Internet and Communications, 16–18 February 2011, pp. 103–108
[302] Petroccia, R., Spaccini, D.: 'A back-seat driver to remotely control the experiments in an underwater acoustic sensor network'. Proc. MTS/IEEE OCEANS 2013, Bergen, Norway, 10–13 June 2013
[303] Pontbriand, C., Farr, N., Preisig, J.W.J., *et al.*: 'Diffuse high-bandwidth optical communications'. Proc. MTS/IEEE OCEANS 2008, Quebec City, QC, Canada, 15–18 September 2008
[304] Doniec, M., Rus, D.: 'Bidirectional optical communication with aquaoptical ii'. 2010 IEEE Int. Conf. Communication Systems, November 2010, pp. 390–394
[305] Cossu, G., Corsini, R., Khalid, A.M., *et al.*: 'Experimental demonstration of high speed underwater visible light communications'. 2013 2nd Int. Workshop on Optical Wireless Communications (IWOW), October 2013, pp. 11–15
[306] Che, X., Wells, I., Dickers, G., *et al.*: 'Re-evaluation of rf electromagnetic communication in underwater sensor networks', *IEEE Commun. Mag.*, 2010, **48**, (12), pp. 143–151
[307] Incio, S.I., Pereira, M.R., Santos, H.M., *et al.*: 'Dipole antenna for underwater radio communications'. 2016 IEEE Third Underwater Communications and Networking Conf. (UComms), August 2016, pp. 1–5
[308] Farr, N., Bowen, A., Ware, J., *et al.*: 'An integrated, underwater optical/acoustic communications system'. Proc. IEEE OCEANS 2010, Sydney, Australia, 24–27 May 2010, pp. 1–9
[309] Moriconi, C., Cupertino, G., Betti, S., *et al.*: 'Hybrid acoustic/optic communications in underwater swarms'. OCEANS 2015 – Genova, May 2015, pp. 1–9
[310] Campagnaro, F., Guerra, F., Favaro, F., *et al.*: 'Simulation of a multimodal wireless remote control system for underwater vehicles'. Proc. 10th ACM Int. Workshop on UnderWater Networks, ser. WUWNet'15, Washington DC, USA, 22–24 October 2015
[311] Park, J.H.: 'LPI techniques in the underwater acoustic channel'. Military Communications Conf. – Communications-Computers: Teamed for the 90's, 1986. MILCOM 1986. IEEE, October 1986, vol. **1**, pp. 10.5.1–10.5.5
[312] van Walree, P.A., Leus, G.: 'Robust underwater telemetry with adaptive turbo multiband equalization', *IEEE J. Ocean. Eng.*, 2009, **34**, (4), p. 645
[313] Lai, L., Liang, Y., Poor, H.V.: 'A unified framework for key agreement over wireless fading channels', *IEEE Trans. Inf. Forensics Sec.*, 2012, **7**, (2), pp. 480–490
[314] Luo, Y., Pu, L., Peng, Z., *et al.*: 'RSS-based secret key generation in underwater acoustic networks: advantages, challenges and performance improvements', *IEEE Commun. Mag.*, 2016, **54**, (2), pp. 32–38
[315] Huang, Y., Zhou, S., Shi, Z., *et al.*: 'Channel frequency response-based secret key generation in underwater acoustic systems', *IEEE Trans. Wirel. Commun.*, 2016, **15**, (9), pp. 5875–5888
[316] Dini, G., Duca, A.L.: 'A secure communication suite for underwater acoustic sensor networks', *Sensors*, 2012, **12**, (11), pp. 15133–15158
[317] Lal, C., Petroccia, R., Conti, M., *et al.*: 'Secure underwater acoustic networks: current and future research directions'. Proc. 3rd IEEE OES Int. Conf. on Underwater Communications and Networking, ser. UComms16, Lerici, Italy, 30 August–1 September 2016
[318] Pelekanakis, K., Cazzanti, L., Zappa, G., *et al.*: 'Decision tree-based adaptive modulation for underwater acoustic communications'. IEEE OES Third Underwater Communications and Networking Conf., ser. UComms'16, 30 August–1 September 2016, pp. 1–5

Document Data Sheet

Security Classification		Project No.
Document Serial No. CMRE-PR-2019-056	**Date of Issue** June 2019	**Total Pages** 22 pp.

Author(s)

Gabriele Ferri, Andrea Munafò, Alessandra Tesei, Paolo Braca, Florian Meyer, Konstantinos Pelekanakis, Roberto Petroccia, João Alves, Christopher Strode, Kevin LePage

Title

Cooperative robotic networks for underwater surveillance: an overview

Abstract

Underwater surveillance has traditionally been carried out by means of surface and undersea manned vessels equipped with advanced sensor systems. This approach is often costly and manpower intensive. Marine robotics is an emerging technological area that enables the development of advanced networks for underwater surveillance applications. In contrast with the use of standard assets, these advanced networks are typically composed of small, low-power, and possibly mobile robots, which have limited endurance, processing and wireless communication capabilities. When deployed in a region of interest, these robots can cooperatively form an intelligent network achieving high performance with significant features of scalability, adaptability, robustness, persistence and reliability. Such networks of robots can be the enabling technology for a wide range of applications in the maritime domain. However, they also introduce new challenges for underwater distributed sensing, data processing and analysis, autonomy and communications. The main thrust of this study is to review the underwater surveillance scenario within a framework of four research areas: (i) underwater robotics, (ii) acoustic signal processing, (iii) tracking and distributed information fusion, and (iv) underwater communications networks. Progress in each of these areas as well as future challenges is presented.

Keywords

Acoustic signal processing, autonomous underwater vehicles, cooperative communication, intelligent networks, mobile robots, surveillance

Issuing Organization

NATO Science and Technology Organization
Centre for Maritime Research and Experimentation

Viale San Bartolomeo 400, 19126 La Spezia, Italy

[From N. America:
STO CMRE
Unit 31318, Box 19, APO AE 09613-1318]

Tel: +39 0187 527 361
Fax:+39 0187 527 700

E-mail: library@cmre.nato.int