

Distributed Information Fusion in Multistatic Sensor Networks for Underwater Surveillance

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Abstract—Surveillance in antisubmarine warfare has traditionally been carried out by means of submarines or frigates with towed arrays. These techniques are manpower intensive. Alternative approaches have recently been suggested using distributed stationary and mobile sensors, such as autonomous underwater vehicles (AUVs). In contrast with the use of standard assets, these small, low-power, and mobile devices have limited processing and wireless communication capabilities. However, when deployed in a spatially separated network, these sensors can form an intelligent network achieving high performance with significant features of scalability, robustness, and reliability. The distributed information FUSION (DIFFUSION) strategy, in which the local information is shared among sensors, is one of the key aspects of this intelligent network. In this paper, we propose two DIFFUSION schemes, in which the information shared among sensors consists of: 1) contacts, generated by the local detection stage and 2) tracks, generated by the local tracking stage. In the first DIFFUSION scheme, contacts are combined at each nodes using the optimal Bayesian tracking based on the random finite set formulation. In the second DIFFUSION scheme, tracks are combined using the track-to-track association/fusion procedure, then a sequential decision based on the association events is exploited. A full validation of the DIFFUSION schemes is conducted by the NATO Science and Technology Organization—Center for maritime research and experimentation during the sea trials Exercise Proud Manta 2012–2013 using real data. Performance metrics of DIFFUSION and of local tracking/detection strategies are also evaluated in terms of time-on-target (ToT) and false alarm rate (FAR). We demonstrate the benefit of using DIFFUSION against the local noncooperative strategies. In particular DIFFUSION improves the level of ToT (FAR) with respect to the local tracking/detection strategies. In particular, the ToT is increased over 90%–95% while the FAR is reduced of two order of magnitude. The problem of communication failures, data not available from the collaborative AUV during certain periods of time, is also investigated. The robustness of DIFFUSION with respect to these communication failures is demonstrated, and the related performance results are reported here. In particular, with 75% of communication failures the ToT is over 90%–95% with a relatively small increase of the FAR with respect to the case of perfect communication.

Index Terms—Collaborative data fusion, antisubmarine warfare, multistatic active sonar, target tracking, underwater sensor networks, autonomous underwater vehicles, real-world experimentation.

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I. INTRODUCTION AND MOTIVATION

AUTONOMOUS systems have a wide range of applications [1], especially in the underwater domain where it is preferable or mandatory to avoid a human presence. Autonomous Underwater Vehicles (AUVs) with sensing capabilities are used in different applications, especially when the autonomy in the operations is of the utmost importance. This is typically the case when difficulties in communication hamper the possibility of sending remote commands to the vehicles during their navigation, for instance see [2]–[5].

Submarine detection and tracking, referred to as Anti-Submarine Warfare (ASW), is one important surveillance underwater application in which AUVs can be effectively used [6]. There are several approaches to ASW which can be mainly divided in passive and active systems. In active ASW systems the echoes revealing the presence of a target are originated by the reflection of an acoustic waveform produced by the surveillance system itself, while in passive systems sound directly produced by the target is recorded. Even in the presence of active sonars, detection/tracking is difficult since it depends on the complex physics of the underwater channel and can be made more difficult by a careful design of submarine shapes, profiles, materials, and by the use of tactical navigation. Active ASW systems can be classified as monostatic, when the acoustic source and receiver are co-located, as opposed to *multistatic* systems in which the sources and the receivers are different entities, spatially separated from one another [7]–[9]. The minimum multistatic configuration, consisting of a single source-receiver pair, is referred to as *bistatic*.

The geometry between source, target, and receiver which yields the best probability of detecting echoes from the target, is referred to as the “glint” geometry, and it strongly depends on the usually poorly known target heading. Moreover, with a monostatic system a clever submarine’s navigation strategy can minimize its sonar cross section with respect to a particular direction, while with a multistatic system this strategy is much more difficult.

Acoustic sources include hull mounted sonars, active sonobuoy sources, towed variable-depth sonars, and fixed sources, while towed line arrays are commonly used as receivers [10]. Traditionally these arrays have been towed by submarines or frigates, however this approach is manpower intensive. More recently, alternative approaches have been suggested in which the system is made of distributed mobile and stationary sensors, such as sonobuoys and

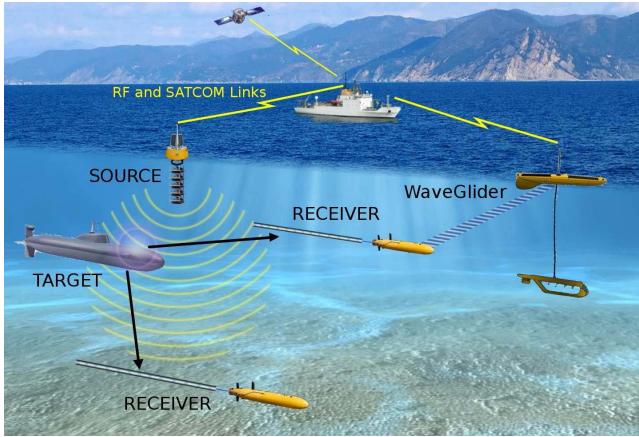


Fig. 1. Sketch of the CMRE cooperative ASW multistatic network. The c^2 is on board of the NRV Alliance. Each AUV acts as receiver of the multistatic setup, towing a passive hydrophone array. The source node can be fixed or mobile, i.e., towed by the NRV. The components of the network (e.g., AUVs, source, c^2 , etc.) communicate using underwater or RF data links. Fixed and mobile gateways, such as wave gliders, are used to guarantee the connectivity of the network.

AUVs [1], [6], [11], [12]. As opposed to the use of standard assets, these small, low-power, and mobile devices have limited on board processing and wireless communication capabilities. Consequently, individual sensors can only perform local computation and, because of the underwater channel limitations, communicate over a short range at low data rates. But when deployed across a spatial domain and properly interconnected, these relatively simple sensors can form an intelligent network achieving high performance with significant features of scalability, robustness, reliability. The concept is to develop autonomous systems providing effective ASW capabilities at a fraction of the cost of traditional assets while providing persistent surveillance of an area. An overview on underwater Wireless Sensor Networks (WSNs) is provided in [1]. This is the solution we have been pursuing at NATO Science and Technology Organization - Centre for Maritime Research and Experimentation (CMRE, formerly known as SACLANTCEN and NURC). In the CMRE underwater network, sensorised AUVs act as autonomous mobile nodes, see Fig. 1. Multistatic sonar systems have the potential to greatly increase ASW coverage and performance. The possibility to use several sources and receivers generates different geometric distributions of source-target-receiver increasing the probability of detection and classification for a target.

However, for an AUV, the ASW scenario is challenging from the tracking point of view. Several clutter-generated tracks may be simultaneously present, with some of them possibly lasting for several pings. In addition, the target may not be observable for some time due to particular sound channel conditions or low probability of detection (e.g. due to a particular aspect angle with respect to the receiver arrays). In addition, in ASW systems based employing AUVs, receiving sensors have limited on board computational capabilities and therefore linear arrays with a conventional (rather than adaptive) beamformer are usually employed. In addition, horizontal line array receivers are cylindrically symmetric; they cannot discriminate if

a detected echo comes from the port or from the starboard, i.e., they suffer from Port–Starboard (PS) ambiguity [13]–[15]. Thus ambiguous tracks may be produced by the on board tracker.

The mobility and the number of the mobile nodes can be used to solve these problems. Their mobility and autonomy can be used to implement data-driven approaches, enabled by the computational power currently available on board the vehicles. Data-driven approaches and autonomous decisions taken by the vehicles can increase the efficiency of missions by deviating from the pre-planned tracklines traditionally used for AUVs in some real world operations [3], [16], [17]. The AUVs can navigate to optimize some metric of interest, such as the signal-to-noise ratio (SNR), the detection probability, or the estimated tracking error over a future horizon [17]–[21] potentially increasing the tracking performance. The nodes can also share locally collected information. For instance, solutions for the PS ambiguity in combination with the data association problem are provided in [13]–[15] where the assumption, that the target of interest is always assumed present, is made.

In this paper we propose a Distributed InFormation FUSION (DIFFUSION) protocol, in which the local information is shared among sensors. We demonstrate that DIFFUSION can bring clear benefits since clutter-generated or ambiguous tracks can be identified and eliminated. On the other hand, tracks originated by targets can be validated and the detection capability of the target can be improved. In particular, we propose and describe two DIFFUSION schemes, in which the information shared in the network consists of *i*) contacts and *ii*) tracks.

The final validation of the proposed approach is performed using real data collected during sea trial experiments, conducted by the NATO CMRE in 2012 and 2013. The NATO Research Vessel (NRV) *Alliance* and CMRE's underwater network with multistatic sonar system have been used during the experimentation. The results of these underwater experimental campaigns are here reported.

Performance metrics are evaluated in terms of Time-on-Target (TOT) and False Alarm Rate (FAR). The TOT is defined as the percentage of time in which the algorithm correctly estimates the target trajectory. The FAR is instead the rate of false target presence declared by the algorithm and normalized by unit of time and space. See more details about TOT and FAR in [22] and [23]. We demonstrate the benefit of using DIFFUSION against local strategies, such as the local detector and the local tracker on board a single AUV. The robustness of DIFFUSION with respect to communication failures is also demonstrated.

The paper is organized as follows. In Sec. II there is a description of the DIFFUSION architectures while the derivation of the DIFFUSION procedures based on detection and track sharing is presented in Sec. III and Sec. IV, respectively. In Sec. V a description of the experiments and the related results are reported. Finally, in Sec. VI the final remarks are presented.

II. DIFFUSION ARCHITECTURES

One problem of a distributed system is that the information contained in the observed data is only locally available

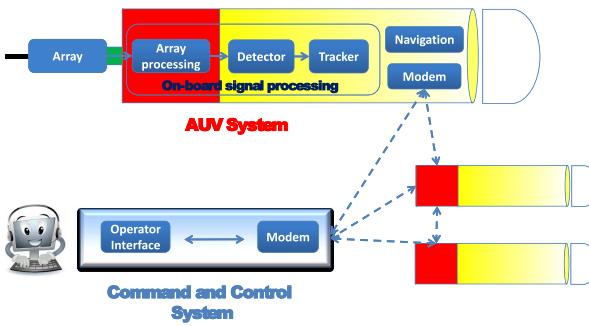


Fig. 2. Sketch of the DIFFUSION scheme, in which the AUVs share information with one another and the c^2 system by using a data link provided by the underwater acoustic modem. The block diagram shows the signal processing chain (array processing, detector, tracker) on board of the AUV.

and must be shared among the AUVs and the Command and Control (c^2) system using an underwater communication system. Unfortunately, underwater acoustic communication suffers from severe limitation in terms of bandwidth, and for this reason very little information can be shared between platforms. The objective is to share as much meaningful information as possible in order to improve the detection/tracking performance of the individual AUVs.

The standard approach to the target tracking problem can be divided in two main parts: *i*) detection and *ii*) tracking [24]. A natural choice for exchanging information is thus to share *i*) detections (often referred as contacts) or *ii*) tracks. An overview of the on board signal processing chain is depicted in Fig. 2. The main blocks are the array processing, the detector, and the tracker. The navigation block is used not only to control the AUV trajectory but also to provide the AUV geolocation. The modem block is dedicated to underwater communication.

In this section we present two DIFFUSION architectures, in which the information provided by each AUV is given by: *i*) detections and *ii*) tracks. Note that both detections and tracks can be also generated by *false* targets (often referred as false alarms and false tracks, respectively) or ghost targets because of the PS ambiguity. The PS ambiguity is the impossibility for the AUV to discriminate port from starboard contacts, this ambiguity complicates the detection and tracking algorithms and may severely degrade performance. In [13] and [14] the target is always assumed to be present and a Bayesian tracking approach is proposed to track the target state in presence of PS ambiguity and measurement origin uncertainty (missed detections and false alarms) [24]. The purpose of DIFFUSION is to provide an improvement in terms of the overall capability of detecting the target (quantified in terms of TOT) and in terms of false alarm reduction (quantified in terms of FAR) with respect to the case in which the information on board the single AUV is available.

In the first DIFFUSION architecture, based on detection sharing, at every time scan k each AUV broadcasts its local detections, position and orientation to the network and receive the same information from other nodes. Each AUV, as well as the c^2 system, updates its posterior distribution of the target state (target presence and position/dynamic) based on

the detections collected by its AUV collaborators. In the case that the communication fails then the AUV updates its posterior based only on its own detections. The posterior distribution is computed numerically by using an *ad hoc* particle filter, detailed in Sec. III.

In the second DIFFUSION architecture, based on track sharing, at every time scan k each AUV broadcasts its local tracks and related covariance matrices to the network and receives the tracks and covariance matrices from other nodes. Each AUV and the c^2 perform a track-to-track association/fusion [24]. Based on the association events a sequential decision rule is used to classify (disambiguate) the local tracks deciding if a track is true or false/ghost. If the AUV geometry is favorable and the target is detected by at least two AUVs this procedure is able to correctly disambiguate the tracks. This architecture is detailed in Sec. IV.

The challenge of DIFFUSION practical implementation is related to the real-time constraint required by the surveillance application. Clearly, as well known in tracking literature, particle filters are among the most demanding techniques in terms of computational effort. For this reason the proposed DIFFUSION particle filtering, which is Bayesian optimal, risks to be unfeasible on low cost AUV technologies. The second DIFFUSION scheme is instead not optimal but very efficient in terms of computational effort.

III. DIFFUSION BASED ON DETECTION SHARING

A network of N_{AUV} AUVs monitoring a certain surveillance region is considered. The objective of the network is to estimate the absence or presence of a target and, in the latter case, its kinematic components at each time scan k .

The target state X_k can be conveniently formalized as a Bernoulli random finite set (RFS) [25]–[27], where $X_k = \{\emptyset\}$ when the target is absent, or $X_k = \{x_k\}$ when the target is present with $x_k = [x_k, \dot{x}_k, y_k, \dot{y}_k]^T$, where the two positions are $x_k^{(p)} = [x_k, y_k]^T$ and $[\dot{x}_k, \dot{y}_k]^T$ are the corresponding velocities. In this work, when the target is present, we assume a nearly constant velocity model [24]:

$$x_k = F_k x_{k-1} + v_k, \quad (1)$$

where F_k is the state transition matrix, and v_k takes into account the target acceleration or unmodeled dynamics.

At each time scan k a set of contacts are observed by the s^{th} AUV, defined by

$$Z_{k,s} = \{z_{k,s,i}\}_{i=1}^{m_{k,s}}, \quad (2)$$

where $m_{k,s}$ is the number of measurements. Given the PS ambiguity problem, $z_{k,s,i}$ in (2) are just the contacts on the port side, since they form a sufficient statistic, because of the deterministic dependence of the starboard contacts on the port contacts [13].

A. Target Presence/Absence

Under the hypothesis of target absence (hypothesis \mathcal{H}_0), the contacts are independent from each others and identically distributed with a known clutter distribution. The set density

of the measurements under \mathcal{H}_0 , at time k and at the s^{th} sensor can be formally written as:

$$f_{k,s}(Z|\mathcal{H}_0) = \mu_c(m; \lambda) \prod_{i=1}^m f^{(c)}(z_i), \quad (3)$$

where $\mu_c(m; \lambda)$ is the probability mass function (PMF) of the clutter cardinality (often assumed as a Poisson PMF with rate λ), and $f^{(c)}(z)$ is probability density function (PDF) of the clutter location (typically modeled as uniform in the region of interest), see further details in [13], [24], and [28]–[31].

When the target is present (hypothesis \mathcal{H}_1), it can be observed with a certain detection probability. This may vary dramatically over the surveillance region, and is in general a function of the receiver array parameters, source parameters, source-target-receiver geometry, and environmental parameters as such as bottom scattering strength, water column and bottom sediment density and sound speed, and bottom and surface roughness and reflection loss. Numerical and/or closed-form acoustic propagation models [32]–[34] are then used to calculate the predicted P_D . We borrow from [15] an acoustic model to predict the detection probability of the target in any position in the surveillance region, taking into account the relevant environmental acoustic effects. This will be key for enhancing the performance of the tracking algorithm, as well as for the path planning optimization proposed in [20].

The aforementioned acoustic model provides us with a detection probability $P_D(\mathbf{x}_k^{(p)}, \mathbf{p}_{k,s}, s_k)$, which is a function on the target position $\mathbf{x}_k^{(p)}$, of the receiver position $\mathbf{p}_{k,s}$ and of the source position s_k . In this work we assume a stationary source, then $s_k = s$ and $P_D(\mathbf{x}_k^{(p)}, \mathbf{p}_{k,s}, s_k) \equiv P_D(\mathbf{x}_k^{(p)}, \mathbf{p}_{k,s})$. Since we assume that at most one target is present, all the other contacts are clutter, independent from the target's state. Then, the set density of data under \mathcal{H}_1 is given by

$$\begin{aligned} f_{k,s}(Z|\mathcal{H}_1) &= \left(1 - P_D(\mathbf{x}_k^{(p)}, \mathbf{p}_{k,s})\right) \mu_c(m; \lambda) \prod_{i=1}^m f^{(c)}(z_i) \\ &\quad + m^{-1} P_D(\mathbf{x}_k^{(p)}, \mathbf{p}_{k,s}) \mu_c(m-1; \lambda) \\ &\quad \times \sum_{j=1}^m f_{k,s}^{(t)}(z_j) \prod_{i \neq j} f^{(c)}(z_i), \end{aligned} \quad (4)$$

where $f_{k,s}^{(t)}(z)$ is the target-originated PDF with PS ambiguity, see details in [13]. In order to make explicit the relation between the target state and the data, eqs. (3) and (4) can be equivalently rewritten as:

$$f_{k,s}(Z|X_k = \{\emptyset\}) = f_{k,s}(Z|\mathcal{H}_0), \quad (5)$$

$$f_{k,s}(Z|X_k = \{\mathbf{x}_k\}) = f_{k,s}(Z|\mathcal{H}_1). \quad (6)$$

B. Optimal Bayesian Tracking

In Bayesian tracking, the objective is to construct the posterior distribution of the target state X_k . Let us denote by $Z_{1:k}^s = [Z_1^s, Z_2^s, \dots, Z_k^s]$ the aggregate in time of the data up to time step k received by the s^{th} AUV. Let us indicated with $\mathcal{N}_{s,k}$ the set of AUVs able to communicate with the s^{th} AUV. The measurements collected by the s^{th} AUV are $Z_k^s = \{Z_{k,i}\}_{i \in \mathcal{N}_{s,k}}$, which is the aggregate of detection sets received from each

AUV $i \in \mathcal{N}_{s,k}$, including its own detections $s \in \mathcal{N}_{s,k}$. The target state posterior of the s^{th} AUV can be thus written as:

$$\mathcal{P}_s(X_k|Z_{1:k}^s) = \frac{\mathcal{L}(Z_k^s|X_k) \mathcal{P}_s(X_k|Z_{1:k-1}^s)}{\mathcal{P}_s(Z_k^s|Z_{1:k-1}^s)}, \quad (7)$$

where $\mathcal{P}_s(X_k|Z_{1:k-1}^s)$ is the prior at time k and $\mathcal{P}_s(Z_k^s|Z_{1:k-1}^s)$ is the scaling factor. Since the sensors are conditionally independent given the target state, the likelihood $\mathcal{L}(Z_k^s|X_k)$ can be factorized as:

$$\mathcal{L}(Z_k^s|X_k) = \prod_{i \in \mathcal{N}_{s,k}} f_{k,i}(Z_{k,i}|\mathbf{x}_k), \quad (8)$$

where $f_{k,i}(Z_{k,i}|X_k)$ is the likelihood of the s^{th} sensor at time k , given in eqs. (5)–(6). We assume that the AUVs have the ability to communicate not only their local detections $Z_{k,i}$, but also AUV positions $\mathbf{p}_{k,s}$ and orientations. Analogously, we can proceed to update the target state posterior at the c^2 .

Unfortunately, closed-form solutions of the posterior distribution (7) are seldom available in practice. As a consequence, one should typically resort to some form of approximation that are both accurate and computationally tractable. Specifically, in this work we focus on the powerful technique of particle filtering to obtain a numerically efficient approximation of (7), [28], [35], [36]. The posterior distribution (7) at time k is represented by

$$\hat{\mathcal{P}}_s(X_k|Z_{1:k}^s) = \begin{cases} w_k^\emptyset, & X_k = \emptyset, \\ \sum_{i=1}^{N_p} w_k^i \delta_{\mathbf{x}_k^i}(\mathbf{x}), & X_k = \{\mathbf{x}\}, \end{cases} \quad (9)$$

where w_k^\emptyset is the weight approximating $\mathcal{P}_s(X_k = \emptyset|Z_{1:k}^s)$, \mathbf{x}_k^i is the i -th sample of the target state, w_k^i is the i -th weight approximating $\mathcal{P}_s(X_k = \{\mathbf{x}_k^i\}|Z_{1:k}^s)$, N_p is the number of particles, $\delta_{\mathbf{x}_0}(\mathbf{x})$ is the delta function located in \mathbf{x}_0 .

Algorithm 1 presents the pseudo-code of the particle filter implementation, where $f(\mathbf{x}_k|\mathbf{x}_{k-1})$ is a Gaussian centered in \mathbf{Fx}_{k-1} with covariance given by \mathbf{Q}_v , $\mathcal{U}_L(\mathbf{x}; z)$ is a 2-D uniform distribution centered in z with length L , p_b and p_s are respectively the target birth and survive probabilities, $N_{Z_k^s} = \sum_{i \in \mathcal{N}_{s,k}} |Z_{k,i}|$ is the total number of contacts at the s^{th} AUV, $\phi_X(\cdot)$ is the RFS transition distribution and $q(\cdot)$ is the importance sampling distribution. Note that the resampling algorithm is standard and given in [37].

C. Detection and Estimation of the Target

In this subsection we describe the estimation procedure for obtaining \widehat{X}_k from the posterior distribution $\mathcal{P}_s(X_k|Z_{1:k}^s)$. As discussed in the RFS literature, see [29], [38], in this work we opt for a two-stage procedure in which first we decide if the target is present or absent and then estimate its state. Given our Bayesian detection framework, the optimal decision rule is formulated as follows [39]

$$\begin{cases} \mathcal{P}_s(X_k \neq \emptyset|Z_{1:k}^s) \geq p_\gamma, & \text{declare } \mathcal{H}_1, \\ \mathcal{P}_s(X_k = \emptyset|Z_{1:k}^s) > 1 - p_\gamma, & \text{declare } \mathcal{H}_0, \end{cases} \quad (10)$$

Algorithm 1 Diffusion Particle Filter

IMPORTANCE SAMPLING

Draw $\mathbf{x}_k^i \sim f(\mathbf{x}_k | \mathbf{x}_{k-1}^i)$, $\forall i = 1, \dots, N_p$;

for $j_s \in \mathcal{N}_{s,k}$ do

 Draw N new samples $\mathbf{x}_k^{N_p+n}$ from $\mathcal{U}_L(\mathbf{x}; \mathbf{z}_{k,j_s,n})$ $\forall n = 1, \dots, |\mathbf{Z}_{k,j_s}|$;

end for

UPDATE

for $i = 1$ to $N_p + N N_{Z_k^s}$ do

$X_k^i = \{\mathbf{x}_k^i\}$, $w_k^i = \mathcal{L}(Z_k^s | X_k^i) \frac{\phi_X(\mathbf{x}_k^i | \mathbf{x}_{k-1}^i)}{q(\mathbf{x}_k^i | \mathbf{x}_{k-1}^i, Z_k^s)} w_{k-1}^i$;

end for

$w_k^\emptyset = \mathcal{L}(Z_k^s | X_k = \emptyset) [(1 - p_b) w_{k-1}^\emptyset + (1 - p_s) (1 - w_{k-1}^\emptyset)]$;

Drop the particles with the lowest $N N_{Z_k^s}$ weights;

NORMALIZATION

$w_t = w_k^\emptyset + \sum_{j=1}^{N_p} w_k^j$; {Total weight}

$w_k^\emptyset = \frac{w_k^\emptyset}{w_t}$; $w_k^i = \frac{w_k^i}{w_t}$, $\forall i = 1, \dots, N_p$;

RESAMPLING

$N_{eff} = \left(\sum_{j=1}^{N_p} w_k^j \right)^{-1}$; {Effective sample size}

if $N_{eff} < N_p T_d$ then

 resampling;

end if

where p_γ is named as target probability threshold. The estimator is then given by

$$\hat{\mathbf{x}}_k = \begin{cases} \{\hat{\mathbf{x}}_k^i\}, & \text{if decided } \mathcal{H}_1, \\ \emptyset, & \text{if decided } \mathcal{H}_0, \end{cases} \quad (11)$$

where $\hat{\mathbf{x}}_k$ is the estimator of the target state. A convenient choice for the target state, optimal in terms of mean square error, is the posterior mean $\hat{\mathbf{x}}_k = \mathbb{E}[\mathbf{x}_k | Z_{1:k}^s]$, where $\mathbb{E}[\cdot]$ is the posterior mean operator.

IV. DIFFUSION BASED ON TRACK SHARING

In this section the DIFFUSION, based on the T2T procedure, is detailed and discussed. The T2T procedure is performed in two steps: the T2T *association* (T2T-A) and the T2T *fusion* (T2T-F) [24]. A local tracker, running on each AUV, is available. At the AUV s , the tracker is feed sequentially by the local detections at each time scan and provides a number of tracks, denoted by $\{\mathbf{x}_{k|k}^{s,i}\}_{i \in \mathcal{T}_k^s}$, and their related covariance

matrices $\{P_{k|k}^{s,i}\}_{i \in \mathcal{T}_k^s}$, where \mathcal{T}_k^s is the set of active tracks at AUV s .

The T2T-A is a procedure which associates the tracks of AUV s_1 , to those of the AUV s_2 . Let us begin assuming that just a single track is active at each AUV: $\mathbf{x}_{k|k}^{s_1,i}$ at s_1 and $\mathbf{x}_{k|k}^{s_2,j}$ at s_2 . The true target states are respectively \mathbf{x}_k^i and \mathbf{x}_k^j for s_1 and s_2 . Let us define:

$$\hat{\Delta}_k^{ij} \triangleq \mathbf{x}_{k|k}^{s_1,i} - \mathbf{x}_{k|k}^{s_2,j}, \quad \Delta_k^{ij} \triangleq \mathbf{x}_k^i - \mathbf{x}_k^j. \quad (12)$$

The *same target* and the *different target* hypotheses, namely \mathcal{H}_{ij} and $\bar{\mathcal{H}}_{ij}$, are formulated as

$$\mathcal{H}_{ij} : \Delta_k^{ij} = 0, \quad \bar{\mathcal{H}}_{ij} : \Delta_k^{ij} \neq 0. \quad (13)$$

The error in the difference of the state estimates is defined as

$$\tilde{\Delta}_k^{ij} = \Delta_k^{ij} - \hat{\Delta}_k^{ij}, \quad (14)$$

with covariance, under the independence assumption,¹ given by

$$\mathbf{T}_k^{ij} = \mathbf{P}_k^{s_1,i} + \mathbf{P}_k^{s_2,j}. \quad (15)$$

The decision is based on the testing rule

$$D_{ij} \triangleq \left(\tilde{\Delta}_k^{ij} \right)^T \left[\mathbf{T}_k^{ij} \right]^{-1} \tilde{\Delta}_k^{ij} \stackrel{\mathcal{H}_{ij}}{\gtrless} D_\alpha, \quad (16)$$

where the threshold D_α is computed such that $P\{D_{ij} > D_\alpha | H_{ij}\} = \alpha$. Exploiting the Gaussian assumption, the threshold corresponds to the $1 - \alpha$ point of the chi-square distribution.

Let us consider the case in which there are multiple tracks on each AUV. Therefore, the previous testing rule must be extended as follows. Assume that s_1 and s_2 AUVs have a set of active tracks $\mathcal{T}_k^{s_1}$, with $N_{s_1} = |\mathcal{T}_k^{s_1}|$, and $\mathcal{T}_k^{s_2}$, with $N_{s_2} = |\mathcal{T}_k^{s_2}|$, respectively. We define the binary assignment variable δ_{ij} , which is unity if the track i of s_1 is associated with the track j of s_2 , and null otherwise. The list of tracks at each site is augmented with a dummy element, indicated with the null index, to incorporate the case in which the track of one AUV should not be associated with any of the tracks of the other AUV. For instance, δ_{i0} represents the case that the track i is not associated. If we assume that the track association events among different track pairs are independent, then the 2-D assignment formulation finds the most likely (joint) T2T-A hypothesis by solving the following constrained optimization [24]

$$\begin{aligned} \min_{\delta_{ij}} \quad & \sum_{i=0}^{N_{s_1}} \sum_{j=0}^{N_{s_2}} \delta_{ij} c_{ij} \\ \text{s. t.} \quad & \sum_{i=0}^{N_{s_1}} \delta_{ij} = 1, \quad j = 1, \dots, N_{s_2}, \\ & \sum_{j=0}^{N_{s_2}} \delta_{ij} = 1, \quad i = 1, \dots, N_{s_1}, \\ & \delta_{ij} \in \{0, 1\}, \quad i = 0, \dots, N_{s_1}, \quad j = 0, \dots, N_{s_2}, \end{aligned} \quad (17)$$

where

$$c_{ij} = -\ln \mathcal{L}_{ij}. \quad (18)$$

For $i, j \geq 1$, \mathcal{L}_{ij} is the likelihood ratio of the two tracks being from the same target versus being from two different targets and is proportional to D_{ij} . For $i = 0$ (or $j = 0$) \mathcal{L}_{ij} is the likelihood ratio of an incomplete assignment, see further details in [24]. The optimization problem of eq. (17) can be solved using standard procedures, *e.g.* the Auction algorithm, linear programming by relaxing the integer constraint, etc. Defining δ_{ij}^* the T2T-A pairs, the fusion target state is computed for all the associated tracks, $\delta_{ij}^* = 1$ $i, j \geq 1$ leading

¹Note that the track estimates $\mathbf{x}_{k|k}^{s_1,i}$ and $\mathbf{x}_{k|k}^{s_2,j}$ are not independent [24]. However, in this work we use this simplification since the procedure to carry out the dependency would require a higher computational load.

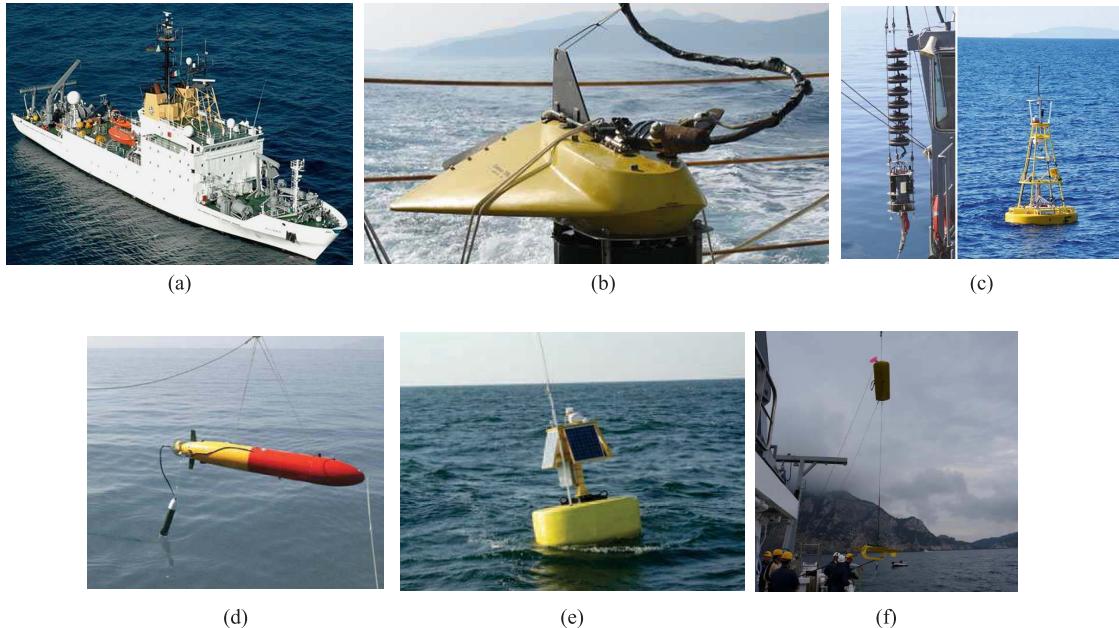


Fig. 3. Main research equipments for the sea trials. (a) NRV Alliance is used as c^2 of the sensor network system. (b) Echo repeater used to simulate an underwater target and towed by the NRV. (c) The DEMUS is the acoustic source of the multistatic network. (d) The OEX-AUV with the BENS towed-array. (e) Acoustic and radio frequency gateway. (f) Wave glider.

to higher accuracy than the individual state estimates. For all the unassociated tracks the fusion system is equivalent to the single sensor.

A. Sequential Decision Based on the T2T-A Events

Because of the PS ambiguity problem, the set of tracks \mathcal{T}_k^s at each AUV is constituted by true tracks and *ghost* tracks. Let us assume that a true track, say i' , is generated by port side contacts then the tracker likely would generate a ghost track, say i'' , by using the symmetric contacts, in terms of bearing, on the starboard side. In principle, by using a linear array there is not a procedure able to disambiguate without a sharp maneuvering of the AUV [13]. Here we propose the T2T-A events as decision statistic to disambiguate.

In general two ambiguous tracks i' and i'' cannot be both true at the same time, unless there are two true targets in exactly the same location relative to the array. In other words one of them is always *ghost*. Let us define the sets of ambiguous tracks $\{\tilde{\mathcal{T}}_k^s, \tilde{\mathcal{T}}_k^s\} = \mathcal{T}_k^s$, with an index operator

$$i'' = g_k(i') \in \tilde{\mathcal{T}}_k^s, \quad \forall i' \in \tilde{\mathcal{T}}_k^s. \quad (19)$$

Define a sequential score function $l_k(i)$, $\forall i \in \mathcal{T}_k^s$ for each track, initialized to zero. If track i is associated with one track of the other AUVs ($\delta_{ij}^* = 1$), then we update the sequential score function as follows

$$l_k(i) = l_{k-1}(i) + 1, \quad (20)$$

$$l_k(g_k(i)) = l_{k-1}(g_k(i)) - 1.$$

When a positive threshold $\gamma \geq 0$ is reached the track is declared to be disambiguated or correct, otherwise when a negative threshold $\gamma^- < 0$ is reached the track is declared ghost,

$$l_k(i) \geq \gamma, \quad \text{Track } i \text{ is declared correct}, \quad (21)$$

$$l_k(i) < \gamma^-, \quad \text{Track } i \text{ is declared ghost}. \quad (22)$$

V. DIFFUSION EXPERIMENTAL RESULTS

In this section the full validation of the DIFFUSION schemes is provided using real data from experiments conducted by NATO CMRE during the sea trials *Exercise Proud Manta 2012* (EXPOMA12) and *Exercise Proud Manta 2013* (EXPOMA13). Specifically, DIFFUSION based on detection sharing is tested using the EXPOMA12 dataset, while the DIFFUSION based on track sharing is tested using the EXPOMA13 dataset.

In EXPOMA12 we simulate the presence of communication failures, in which an AUV does not receive information from its collaborator. In the case of perfect communication, the AUVs, as well as the c^2 , perform equivalently because they use the same data. In EXPOMA13 we use the data correctly received at the c^2 during the experimentation. Coherently, we define the communication error rate (CER) as the percent of communication failures.

In the next subsections we briefly describe the experiments conducted during EXPOMA12 and EXPOMA13 and the technical details of the main research equipments (see Fig. 3) which constitute the CMRE cooperative ASW multistatic network schematically depicted in Fig. 1. Then, we report the results obtained by adopting the DIFFUSION schemes.

A. CMRE Cooperative ASW Multistatic Network

As the acoustic source, we used the Deployable Experimental Multi-static Undersea Surveillance System DEMUS [40]. The source is bottom-tethered and was not moved during the experiments. The source transmitted a hyperbolic frequency modulated (HFM) sweep with 48 s ping repetition rate. The DEMUS source was equipped with a modem to enable remote activation via underwater acoustic communications, and a radio buoy to allow wireless activation

and monitoring of the source, as well as GPS synchronization for timing and accurate position estimates.

The vehicles used as receiving nodes of the multistatic network were two Ocean Explorer (OEX) AUVs (shown in Fig. 3(d)). These vehicles are approximately 4.3 m long and 0.53 m wide. They can reach a speed of 1 m/s with a maximum operating depth of 300 m. The OEX AUVs are both deployed with the BENS slim towed array SLITA [11]. The arrays are deployed approximately 3.5 m behind the vehicle. In the experiments both vehicles suffered from PS ambiguity, as discussed before.

AUVs communicated between each other and with the c^2 centre acoustically. Each vehicle was equipped with a 7/17 kHz Evologics [41] low-frequency modem. The adopted channel access method is the Time Division Multiple Access (TDMA).

To communicate from c^2 centre with the vehicles a gateway buoy is deployed. The gateway buoy has a radio link with the c^2 centre and is equipped with an acoustic modem. Starting from EXPOMA13, a Waveglider autonomous surface vehicle [42] has been used in the network as an additional gateway. The Waveglider's mobility is used to position it in favorable locations to improve the communication with the vehicles. With this configuration, four nodes are present in the communication scheme and the used TDMA frame was 54 s. The vehicles usually sends messages containing navigation data and information related to their operative state. When contacts and/or tracks are present, the AUVs try to send them in a message containing the five highest SNR contacts and in a message containing the three longest tracks produced by the tracker. Given the available bandwidth and the messages to be sent, when present, these two messages are sent with a maximum delay of one TDMA frame (in the frame later to their production).

All the assets were deployed from the NRV Alliance. The vessel acted as the c^2 centre during the experiments. The discussed datasets were collected by using an echo-repeater (ER) as a target.

The ER was towed by the NRV Alliance, and recorded the waveforms received following the DEMUS transmissions, then re-transmitted the recorded signals with a user-specified amplitude gain after a user-specified delay.

During the experiments described in this work, the echo repeater re-broadcast the incoming sonar signal with a tunable gain over the received level. This gain serves as a substitute for the target sonar cross-section or reflectivity.

1) Auv Control System: The AUV control system is based on the “backseat-driver” paradigm: a backseat computer executes the processes managing the mission and produces commands for a frontseat computer in charge of the low-level vehicle control [43].

The software architecture running on the vehicles is based on MOOS-IvP [43]. MOOS-IvP is an open source C++ framework for providing autonomy to robotic platforms, in particular marine vehicles. MOOS-IvP is based on the publish/subscribe paradigm: a community of processes subscribe to receive and publish variables from/to a database (MOOSDB). For the management and control of vehicles, the

MOOS framework works according to the backseat-driver and fits with the described hardware: MOOS processes managing the mission run on the backseat computer receiving data from/issuing commands to the frontseat computer. The IvP Helm is a MOOS application that enables behaviour-based autonomy [43]. A behaviour is a self-contained vehicle control law that achieves and/or maintain goals [44]. Behaviours can run simultaneously and can be grouped into behaviour sets, which are active based on certain conditions. The IvP Helm is able to reconcile the different active behaviours outputs by using interval programming technique. It combines the objective functions generated by the different active behaviours to produce the commands for the frontseat controller, specifically speed, heading and depth commands. The different behaviours offer a set of navigation primitives, such as waypoint navigation, racetracks or collision avoidance. These are the building blocks to create the AUV missions.

In the MOOS framework, the signal processing software is run [6], [45]. At each ping, *pProcessSlitaBB*, a MOOS front-end to the active sonar signal processing algorithm libraries, receives the acoustic data coming from the array and acquired by the frontseat computer, and produces the contacts (range and bearing data). In particular, it executes the beamforming, matched filtering, normalization and finally creates the contacts. Contacts are fed to the on board tracker process, in this case the CMRE multi-hypothesis tracker (MHT) [46]. The tracker processes the contact data, first geolocating them using the source location and the array location/heading angle. Then it combines (spatially) related contacts over time, generating tracks.

During the two described experiments, pre-planned racetracks were executed by the AUVs. Pre-planned tracklines assure coverage of the area with the area coverage timing computable prior the experiment. These features were important to fulfill the mission requirements.

B. Exercise Proud Manta 2012

The EXPOMA12 was held in the Mediterranean Sea off the coast of Sicily, Italy during February–March 2012. The setup of the experiment is reported in Figs. 4–5, where we depict the location of the DEMUS source (yellow diamond), position of AUVs, *Harpo* (blue square) and *Groucho* (green square), and the trajectory of the target (black dashed line). The ER towed by the NRV Alliance is used in the experiment as a reproducible and controllable target.

The DEMUS is located at (12.3 km, 23.2 km). The target sails from the location (16.5 km, 16.9 km) to (17.2 km, 9.8 km) and then goes to (11.3 km, 15.8 km). The AUVs sail south-east of the source position and the target trajectory. The duration of the experiment is approximately two hours. Further details about the experimental setup are also available in [13].

A key element of this procedure is that the SNR, and consequently the detection probability at each AUV, depends on the geometry of the bistatic system and on the environment, e.g. multipath time spread, reverberation, bathymetry, sound speed, see further details in [13], [15], [19], and [20].

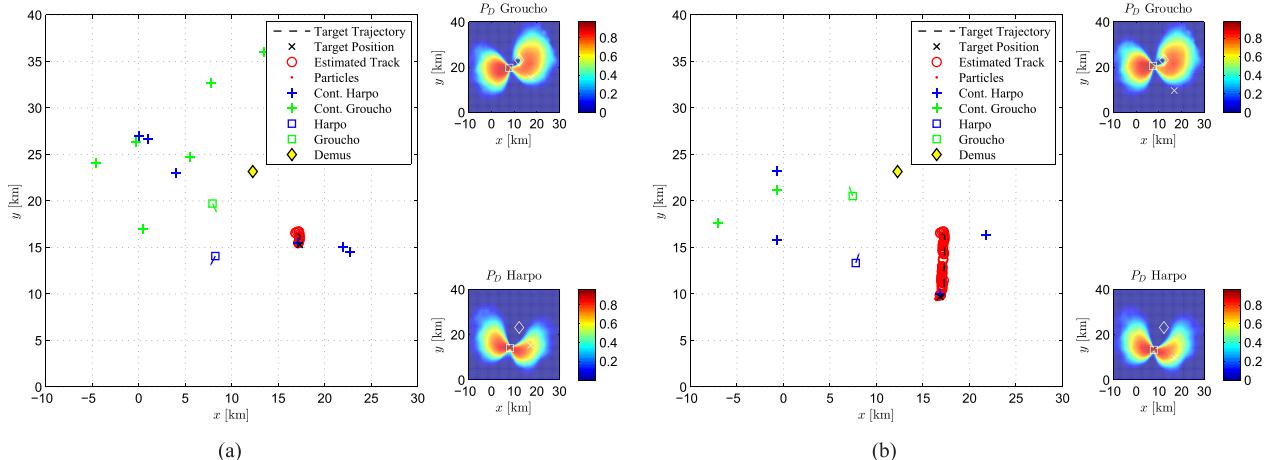


Fig. 4. Sea trial EXPOMA12. Behaviour of the DIFFUSION scheme, based on detection sharing and with perfect communication, using the EXPOMA12 data set, with the detection probability of Harpo and Groucho provided by the acoustic model. Time scan $k = 15$ and $k = 75$. Right-side detection detection probability map of Harpo and Groucho at time scan k , Groucho and Harpo positions (white square ‘□’), source position (white diamond ‘◇’). Left-side we report the target trajectory (dashed black line), current target position (‘x’), estimated target track at time k (red ‘o’), Harpo contacts at time k (blue ‘+’), Groucho contacts at time k (green ‘+’), Harpo position at time k (blue square ‘□’), Groucho position at time k (green square ‘□’), DEMUS position (yellow diamond ‘◇’). (a) $k = 15$. (b) $k = 75$.

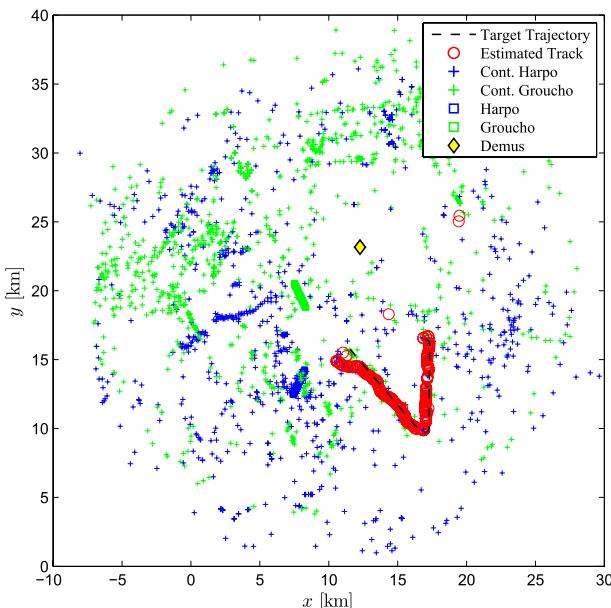


Fig. 5. Sea trial EXPOMA12. Results of the DIFFUSION scheme, based on detection sharing and with perfect communication, using the detection probability of Harpo and Groucho provided by the acoustic model. We report the target trajectory (dashed black line), the estimated target trajectory (red 'o'), overall Harpo contacts (blue '+'), overall Groucho contacts(green '+'), Harpo trajectory (blue square '□'), Groucho trajectory (green square '□'), DEMUS position (yellow diamond '◇').

The detections of each AUV are combined by using DIFFUSION, defined in Sec. III. The DIFFUSION is implemented by a particle filtering strategy derived in Sec. III-B.

In Fig. 4, we report the behaviour of DIFFUSION in which the detection probability of each AUVs is not constant over the surveillance region. Fig. 4(a)-(b) (right-side) show the so-called blanking region between the AUV and the source and also the degradation of the detection probability (< 0.3) near the edges of the surveillance region. However, note that the target is mostly moving in the region where the detection probability is high ($\approx 0.7 - 0.9$).

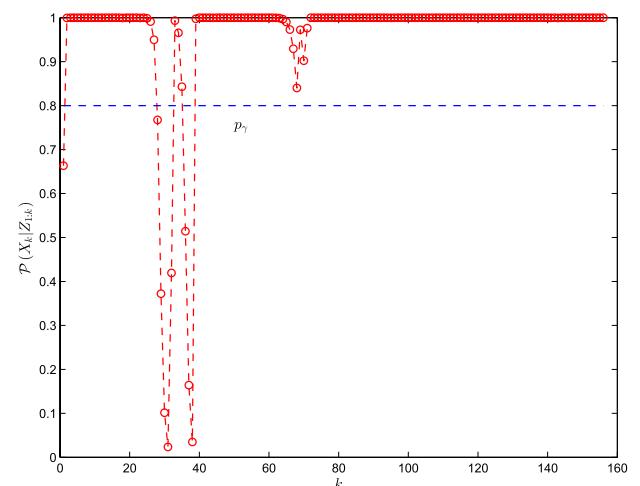


Fig. 6. Sea trial EXPOMA12. Posterior target presence probability of the DIFFUSION scheme, based on detection sharing and with perfect communication, versus the time k . The decision threshold $p_y = 0.8$ is also reported.

TABLE I
 SEA TRIAL EXPOMA12. COMPARISON IN TERMS OF ToT AND FAR
 AMONG DIFFUSION WITH PERFECT COMMUNICATION (CER = 0),
 CER = 75% AND DETECTOR ON BOARD THE SINGLE AUV

	CER %	FAR [$s^{-1}km^{-2}$]	ToT %
Detector Harpo	/	$7.5 \cdot 10^{-5}$	78
Detector Groucho	/	$9.1 \cdot 10^{-5}$	53
DIFFUSION Harpo	75	$5.8 \cdot 10^{-7}$	95
DIFFUSION Groucho	75	$6.7 \cdot 10^{-7}$	91
DIFFUSION	0	$2.5 \cdot 10^{-7}$	94

Using the proposed procedure we are able to correctly estimate the target trajectory and to reject most of the ghost and false contacts, see Fig. 5. In Fig. 6 the posterior target presence probability is depicted. It is worthwhile to note that for $25 < k < 40$ the target is erroneously considered absent, this is caused by the fact that there is a mismatch between the expected AUV detection probability and the true one. This problem can be overcomed using an adaptive tracking strategy developed in [48] and [49]. In Tab. I we report the

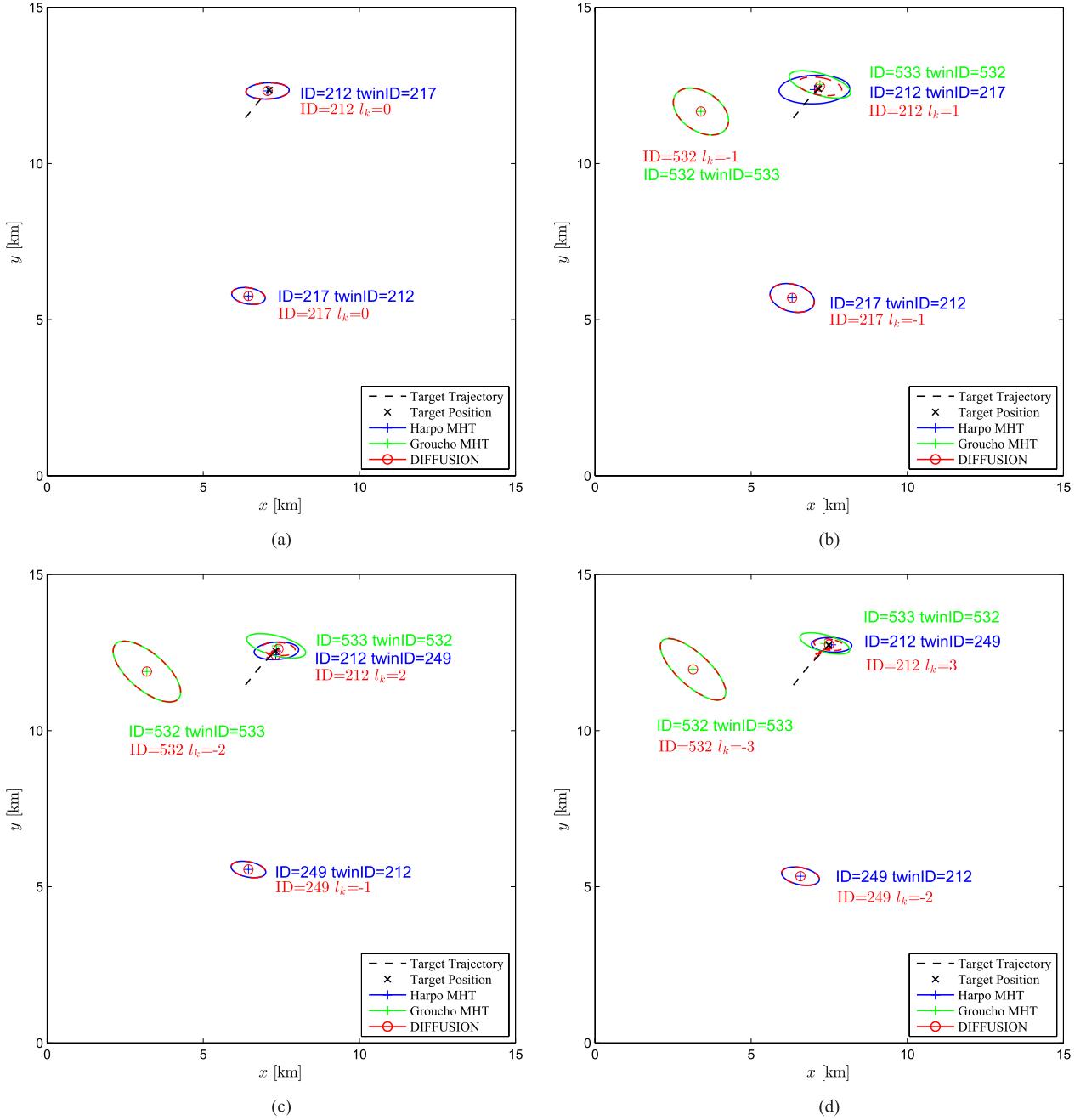


Fig. 7. Sea trial EXPOMA13. Behaviour of the DIFFUSION scheme, based on track sharing. Time scan $k = 86, 87, 90, 93$. We report the target trajectory (dashed black line), current target position ('x'), current position and related covariance of the tracks on board AUVs (dashed blue for Harpo and dashed green for Groucho) and the fused tracks using DIFFUSION (dashed red). The track ID is reported, as well as the ambiguous ID referred as twinID. The Association events are present in time scan $k = 87, 90, 93$ leading to ID = 212 to be declared as target by the DIFFUSION scheme. (a) $k = 86$. (b) $k = 87$. (c) $k = 90$. (d) $k = 93$.

performance of the DIFFUSION scheme in terms of TOT and FAR. The detector on board of AUVs is able to correctly declare the target presence 78% (TOT of Harpo) and 53% (TOT of Groucho) of the overall target time at the cost of FAR = $7.5 \cdot 10^{-5}$ (Harpo) and FAR = $9.1 \cdot 10^{-5}$ (Groucho). The use of the DIFFUSION collaboration among AUVs is able to sensibly increase the performance reducing the FAR of two order of magnitude and increasing the TOT over the 90%. Specifically when there is a perfect communication ($CER = 0$) the TOT for both AUVs is 94% with FAR = $2.5 \cdot 10^{-7}$ while when the communication is affected by remarkable issues,

$CER = 75\%$, the DIFFUSION exhibits still good performance, TOT = 95% and TOT = 91% for respectively Harpo and Groucho, but at the price of an increase of the FAR, $5.8 \cdot 10^{-7}$ for Harpo and $6.7 \cdot 10^{-7}$ for Groucho.

C. Exercise Proud Manta 2013

The ExPOMA13 was held in the Mediterranean Sea off the coast of Sicily, Italy during February-March 2013. The ER towed by the NRV Alliance is used in the experiment as a reproducible and controllable target. We have two trajectories

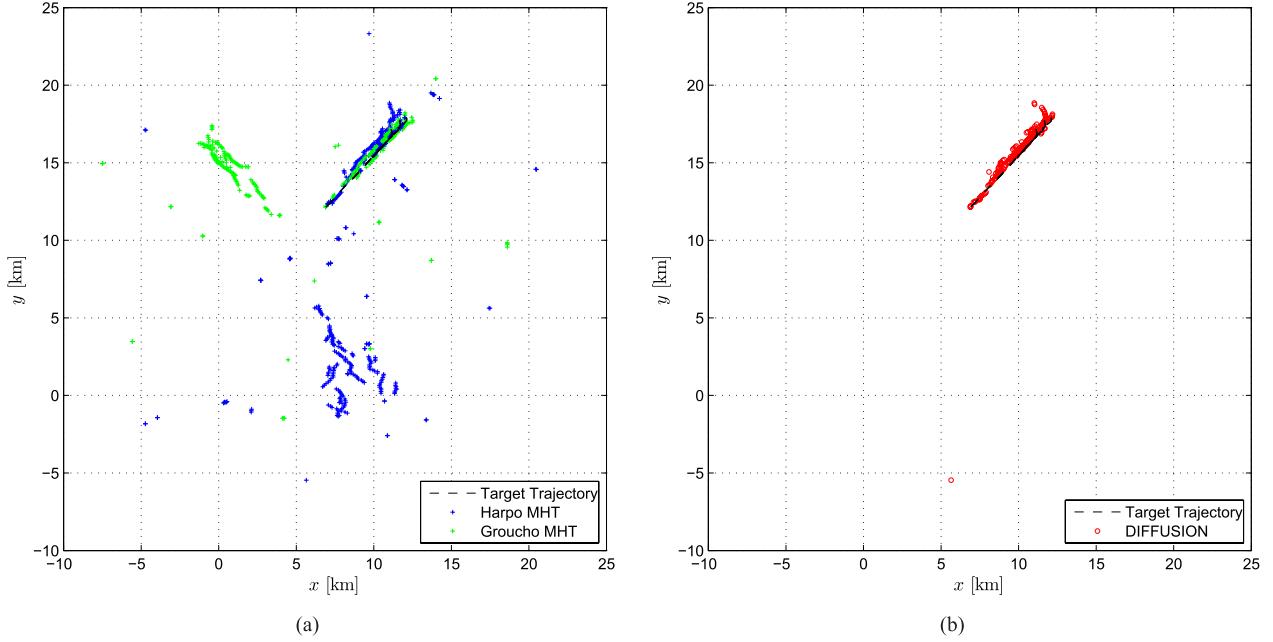


Fig. 8. Sea trial ExPOMA13. Results of the DIFFUSION scheme, based on tracks collected at c^2 on board of the NRV. On the left side, we report the target trajectory (dashed black line), overall Harpo tracks (blue '+'), overall Groucho tracks (green '+'). On the right side, we report the target trajectory (dashed black line) and the DIFFUSION tracks (red circles "o") generated at the c^2 .

of the target, each of them is about one and a half hour. In the first trajectory the target sails from the location (7 km, 12 km) to (11 km, 17 km) and finally goes to (10 km, 16 km), in the second one the target sails from the location (10 km, 15 km) to (12 km, 18 km) and finally goes to (8 km, 13 km).

The DIFFUSION based on track sharing is adopted here, in which the tracks collected by AUVs during the experiment are combined at the c^2 on board of the NRV Alliance. The CER of the AUVs observed at the c^2 was quite good, around 10% for Harpo and 30% for Groucho.

In Fig. 7 we report the behaviour of the DIFFUSION scheme. In time scan $k = 86$, Fig. 7(a), only two active tracks from Harpo are available, consequently DIFFUSION tracks are the same of Harpo with a null score. The DIFFUSION ID is taken by the set of Harpo ID in this case. In time scan $k = 87$, Fig. 7(b), two tracks are provided by Groucho. An association event between ID = 212 of Harpo and ID = 533 of Groucho is observed. Given that ID = 212 and ID = 533 have ambiguous tracks respectively ID = 217 and ID = 532 the association event entails that $l_k(212) = 1$ and $l_k(217) = l_k(532) = -1$. In time scan $k = 90$, Fig. 7(c), and $k = 93$, Fig. 7(d), the same association event is observed leading finally to $l_k(212) = 3$. In time scan $k = 90$ the track ID = 217 is substituted by track ID = 249, then finally at scan $k = 93$ we have $l_k(249) = -2$, $l_k(532) = -3$.

Using DIFFUSION we are able to correctly estimate the target trajectory and to reject most of the ghost and false contacts, see Fig. 8. In Tab. II a comparison is reported in terms of TOT and FAR among the DIFFUSION scheme and the tracker on board the vehicles. In this case we report an increment of the TOT ($\gamma = 0$) from the local tracker 83 – 70% (Harpo and Groucho) to 92% reducing the FAR

TABLE II
EXPOMA13. COMPARISON IN TERMS OF TOT AND FAR AMONG DIFFUSION AND MHT ON BOARD THE SINGLE AUV

	γ	FAR [$s^{-1}km^{-2}$]	TOT %
MHT Harpo	/	$1.6 \cdot 10^{-5}$	83
MHT Groucho	/	$1.2 \cdot 10^{-5}$	70
DIFFUSION	0	$0.9 \cdot 10^{-5}$	92
DIFFUSION	1	$1.3 \cdot 10^{-7}$	85
DIFFUSION	2	$6.4 \cdot 10^{-8}$	78
DIFFUSION	3	$6.4 \cdot 10^{-8}$	72

from $1.2 - 1.6 \cdot 10^{-5}$ to $0.9 \cdot 10^{-5}$. Increasing γ we reduce the FAR of two orders of magnitude by decreasing the TOT to a level of 82% and of three orders of magnitude by decreasing the TOT to a level of 78 – 72%.

VI. CONCLUSION

In this paper we report recent advances in anti-submarine warfare applications using a multistatic network of AUVs. In particular we propose two distributed information fusion (DIFFUSION) schemes, in which the information in the form of contacts and tracks is shared among the AUVs and the command and control.

A full validation of the DIFFUSION schemes using real-world experiments conducted by the NATO Science and Technology Organization – Centre for Maritime Research and Experimentation, during the sea trials *Exercise Proud Manta 2012-2013*, is reported. Significant performance improvements of DIFFUSION schemes are observed in terms of both TOT and FAR against the use of a single AUV asset. Specifically, the TOT is increased over 90 – 95% while the FAR is reduced of two order of magnitude. The robustness of

DIFFUSION with respect to communication failures is also demonstrated, and the related performance results are reported in this paper. Specifically, with 75% of communication failures the TOT is over 90 – 95% with a relatively small increase of the FAR.

Possible directions for future studies include the adaptive AUVs deployment and dynamics, exploiting techniques like dynamic programming and stochastic control. Considering the shallow water environment the tracker can be also enhanced using optimization strategies to maximize the target detection probability. Another future work involves the use of a bandwidth efficient *fully distributed* target tracking collaborative strategy.

REFERENCES

- [1] I. F. Akyildiz, D. Pompili, and T. Melodia, "Underwater acoustic sensor networks: Research challenges," *Ad Hoc Netw.*, vol. 3, no. 3, pp. 257–279, Mar. 2005.
- [2] D. R. Yoerger, M. Jakuba, A. M. Bradley, and B. Bingham, "Techniques for deep sea near bottom survey using an autonomous underwater vehicle," *Int. J. Robot. Res.*, vol. 26, no. 1, pp. 41–54, Jan. 2007.
- [3] G. Ferri, M. V. Jakuba, and D. R. Yoerger, "A novel trigger-based method for hydrothermal vents prospecting using an autonomous underwater robot," *Auto. Robots*, vol. 29, no. 1, pp. 67–83, Jul. 2010.
- [4] A. A. Bennett and J. J. Leonard, "A behavior-based approach to adaptive feature detection and following with autonomous underwater vehicles," *IEEE J. Ocean. Eng.*, vol. 25, no. 2, pp. 213–226, Apr. 2000.
- [5] S. T. Tripp, "Autonomous underwater vehicles (AUVs): A look at coast guard needs to close performance gaps and enhance current mission performance," USCG Res. Develop. Center Studies, Groton, CT, USA, Tech. Rep. 0704-0188, 2006.
- [6] M. J. Hamilton, S. Kemna, and D. Hughes, "Antisubmarine warfare applications for autonomous underwater vehicles: The GLINT09 sea trial results," *J. Field Robot.*, vol. 27, no. 6, pp. 890–902, Nov./Dec. 2010.
- [7] S. Coraluppi, "Multistatic sonar localization," *IEEE J. Ocean. Eng.*, vol. 31, no. 4, pp. 964–974, Oct. 2006.
- [8] R. Georgescu and P. Willett, "The GM-CPHD tracker applied to real and realistic multistatic sonar data sets," *IEEE J. Ocean. Eng.*, vol. 37, no. 2, pp. 220–235, Apr. 2012.
- [9] H. Cox, "Fundamentals of bistatic active SONAR," in *Underwater Acoustic Data Processing*, Y. T. Chan, Ed. Norwood, MA, USA: Kluwer, 1989.
- [10] S. G. Lemon, "Towed-array history, 1917–2003," *IEEE J. Ocean. Eng.*, vol. 29, no. 2, pp. 365–373, Apr. 2004.
- [11] A. Maguer, R. Dymond, M. Mazzi, S. Biagini, and S. Fioravanti, "SLITA: A new slim towed array for AUV applications," in *Proc. Acoust.*, 2008, pp. 141–146.
- [12] A. Baldacci and G. Haralabus, "Signal processing for an active sonar system suitable for advanced sensor technology applications and environmental adaptation schemes," in *Proc. 14th Eur. Signal Process. Conf. (EUSIPCO)*, Sep. 2006, pp. 1–5.
- [13] P. Braca, P. Willett, K. Lepage, S. Marano, and V. Matta, "Bayesian tracking in underwater wireless sensor networks with port-starboard ambiguity," *IEEE Trans. Signal Process.*, vol. 62, no. 7, pp. 1864–1878, Apr. 2014.
- [14] P. Braca, K. Lepage, P. Willett, S. Marano, and V. Matta, "Particle filtering approach to multistatic underwater sensor networks with left-right ambiguity," in *Proc. 16th Int. Conf. Inf. Fusion (FUSION)*, Istanbul, Turkey, Jul. 2013, pp. 266–271.
- [15] R. Goldhahn, P. Braca, K. D. LePage, P. Willett, S. Marano, and V. Matta, "Environmentally sensitive particle filter tracking in multistatic AUV networks with port-starboard ambiguity," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, Florence, Italy, May 2014, pp. 1458–1462.
- [16] K. Rajan, "The role of deliberation (and AI) in marine robots," in *Proc. Workshop Marine Robot., Looking Crystal Ball, Eurocast*, Gran Canaria, Spain, Feb. 2013, pp. 1–7.
- [17] G. Ferri, A. Munafò, R. Goldhahn, and K. LePage, "A non-myopic, receding horizon control strategy for an AUV to track an underwater target in a bistatic sonar scenario," in *Proc. CDC*, Los Angeles, CA, USA, Dec. 2014, pp. 5352–5358.
- [18] K. LePage, "An SNR maximization behavior for autonomous AUV control," in *Proc. 10th Eur. Conf. Underwater Acoust.*, Istanbul, Turkey, 2010, pp. 1–8.
- [19] R. Goldhahn, P. Braca, and K. LePage, "Environmentally sensitive behaviours for collaborating autonomous underwater vehicles in multistatic surveillance networks," NATO, La Spezia, Italy, Tech. Rep. CMRE-FR-2013-012, Nov. 2013.
- [20] P. Braca, R. Goldhahn, K. D. LePage, S. Marano, V. Matta, and P. Willett, "Cognitive multistatic AUV networks," in *Proc. 17th Int. Conf. Inf. Fusion (FUSION)*, Salamanca, Spain, Jul. 2014, pp. 1–7.
- [21] G. Ferri, A. Munafò, R. Goldhahn, and K. LePage, "Results from COLLAB13 sea trial on tracking underwater targets with AUVs in bistatic sonar scenarios," in *Proc. Oceans*, St. John's, NL, Canada, Sep. 2014, pp. 1–9.
- [22] S. Maresca, P. Braca, J. Horstmann, and R. Grasso, "Maritime surveillance using multiple high-frequency surface-wave radars," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 8, pp. 5056–5071, Aug. 2014.
- [23] G. Vivone, P. Braca, and J. Horstmann, "Knowledge-based multitarget ship tracking for HF surface wave radar systems," *IEEE Trans. Geosci. Remote Sens.*, vol. 53, no. 7, pp. 3931–3949, Jul. 2015.
- [24] Y. Bar-Shalom, P. K. Willett, and X. Tian, *Tracking and Data Fusion: A Handbook of Algorithms*. Storrs, CT, USA: YBS Pub., 2011.
- [25] B.-T. Vo, B.-N. Vo, and A. Cantoni, "The cardinality balanced multi-target multi-Bernoulli filter and its implementations," *IEEE Trans. Signal Process.*, vol. 57, no. 2, pp. 409–423, Feb. 2009.
- [26] A. Gning, B. Ristic, and L. Mihaylova, "Bernoulli particle/box-particle filters for detection and tracking in the presence of triple measurement uncertainty," *IEEE Trans. Signal Process.*, vol. 60, no. 5, pp. 2138–2151, May 2012.
- [27] B. Ristic, B.-T. Vo, B.-N. Vo, and A. Farina, "A tutorial on Bernoulli filters: Theory, implementation and applications," *IEEE Trans. Signal Process.*, vol. 61, no. 13, pp. 3406–3430, Jul. 2013.
- [28] P. Braca, S. Marano, V. Matta, and P. Willett, "A linear complexity particle approach to the exact multi-sensor PHD," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, May 2013, pp. 4061–4065.
- [29] P. Braca, S. Marano, V. Matta, and P. Willett, "Asymptotic efficiency of the PHD in multitarget/multisensor estimation," *IEEE J. Sel. Topics Signal Process.*, vol. 7, no. 3, pp. 553–564, Jun. 2013.
- [30] P. Braca, S. Marano, V. Matta, and P. Willett, "Multitarget-multisensor ML and PHD: Some asymptotics," in *Proc. 15th Int. Conf. Inf. Fusion (FUSION)*, Singapore, Jul. 2012, pp. 2347–2353.
- [31] P. Braca, M. Guerriero, S. Marano, V. Matta, and P. Willett, "Selective measurement transmission in distributed estimation with data association," *IEEE Trans. Signal Process.*, vol. 58, no. 8, pp. 4311–4321, Aug. 2010.
- [32] C. H. Harrison, "Closed-form expressions for ocean reverberation and signal excess with mode stripping and Lambert's law," *J. Acoust. Soc. Amer.*, vol. 114, no. 5, pp. 2744–2756, 2003.
- [33] C. H. Harrison, "Fast bistatic signal-to-reverberation-ratio calculation," *J. Comput. Acoust.*, vol. 13, no. 2, pp. 317–340, Jun. 2005.
- [34] C. H. Harrison, "Target time smearing with short transmissions and multipath propagation," *J. Acoust. Soc. Amer.*, vol. 130, no. 3, pp. 1282–1286, 2011.
- [35] C. Kreucher, K. Kastella, and A. O. Hero, "Multitarget tracking using the joint multitarget probability density," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 41, no. 4, pp. 1396–1414, Oct. 2005.
- [36] B.-N. Vo, S. Singh, and A. Doucet, "Sequential Monte Carlo methods for multitarget filtering with random finite sets," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 41, no. 4, pp. 1224–1245, Oct. 2005.
- [37] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking," *IEEE Trans. Signal Process.*, vol. 50, no. 2, pp. 174–188, Feb. 2002.
- [38] R. P. S. Mahler, *Statistical Multisource-Multitarget Information Fusion*. Norwood, MA, USA: Artech House, 2007.
- [39] H. V. Poor, *An Introduction to Signal Detection and Estimation*. New York, NY, USA: Springer, 1988.
- [40] R. Been, D. T. Hughes, and A. Vermeij, "Heterogeneous underwater networks for ASW: Technology and techniques," in *Proc. UDT Eur.*, Glasgow, U.K., Jun. 2008. [Online]. Available: http://www.cmre.nato.int/about-cmre/fact-sheets/doc_download/644-heterogeneous-underwater-networks-for-asw-technology-and-techniques
- [41] [Online]. Available: <http://www.evologics.de/>
- [42] [Online]. Available: <http://liquidr.com/>
- [43] [Online]. Available: <http://oceania.mit.edu/moos-ivp/pmwiki/pmwiki.php>

- [44] R. Arkin, *Behavior-Based Robotics*. Cambridge, MA, USA: MIT Press, 1998.
- [45] S. Kemna, M. J. Hamilton, D. T. Hughes, and K. D. LePage, "Adaptive autonomous underwater vehicles for littoral surveillance," *Intell. Service Robot.*, vol. 4, no. 4, pp. 245–258, Oct. 2011.
- [46] S. Coraluppi and C. Carthel, "Distributed tracking in multistatic sonar," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 41, no. 3, pp. 1138–1147, Jul. 2005.
- [47] G. Papa, P. Braca, S. Horn, S. Marano, V. Matta, and P. Willett, "Adaptive Bayesian tracking with unknown time-varying sensor network performance," in *Proc. 40th IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Brisbane, Qld., Australia, 2015.
- [48] G. Papa, P. Braca, S. Horn, S. Marano, V. Matta, and P. Willett, "Adaptive Bayesian tracking under time-varying target detection capability of sensor networks with measurement origin uncertainty," *IEEE Trans. Signal Process.*, to be published.



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