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# A market-based task allocation framework for autonomous underwater surveillance networks

Gabriele Ferri, Andrea Munafò, Alessandra Tesei, Kevin LePage

***Abstract*— Realisation of underwater robotic surveillance networks raises several challenges for marine robotics. The underwater scenario is typically characterised by intermittent and unreliable communication. This makes it challenging to develop task allocation schemes suited to work effectively in underwater surveillance applications. We propose a market-based approach to task allocation, which works in a completely distributed way. Through periodic auctions, the algorithm achieves the dynamic assignment of robots to tasks throghout the mission. There is no central auctioneer and any robot becomes an auctioneer when it intents to execute a task. Through periodic auctions, all the robots are sequentially allocated to the tasks. The algorithm is designed to increase the robustness to poor communication and to allow task reallocation, to adapt the allocation to the evolving scenario. Results from computer simulations are reported that support the proposed approach. An Anti-Submarine Warfare application is considered to test the scheme. In this application, the surveillance of areas of different dimensions has to be accomplished by a team of AUVs.**

## I. Introduction

Recent advances in marine robotics suggest that Marine Unmanned Systems (MUS) can be effectively used in underwater surveillance networks [1], [2]. Today's robots offer the promise to guarantee persistent monitoring at lower costs than traditional approaches, which consist in statically deployed sensors, or are based on the use of expensive and time consuming ship-based operations. 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.

Robotic networks can take advantage of the presence of both static and mobile nodes [2], [3]. Static nodes can 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 the changing environmental and mission conditions. This results in the possibility for the network to efficiently adapt to evolving scenarios increasing its reconfigurability, reliability and robustness.

At NATO STO-Centre for Maritime Research and Experimentation (CMRE), we have been pursuing this approach [4]–[7] developing and demonstrating at sea a robotic network for Anti-Submarine Warfare (ASW) which embodies a complete multi-static active sonar system (see Fig. 1). The network is composed of one or more active sources (transmitters), which transmit signals (pings), which once reflected off some objects can be recorded by one or more receivers that are mounted on-board AUVs.

The cooperation among the nodes has the potential to increase the network effectiveness. Communication becomes therefore central for the network operations. Data exchange between the nodes allows data fusion [8], which can improve target detection and tracking. It is also fundamental to solve the Multi Robot Task Allocation (MRTA) problem [9], [10].

Multi-Robot Task Allocation (MRTA) consists in finding an optimal assignment of each team member to one or more tasks which compose a general mission, optimising a defined team utility function. In its simplest formulation (each task can be assigned to exactly one robot and one robot cannot be assigned to more than one task), the MRTA becomes an instance of the Optimal Assignment Problem (OAP) [9]. The Optimal Assignment Problem can be solved in a centralised way by using the Hungarian method [9] or in a distributed fashion by using the auction algorithm [11]. The relaxation of the constraints of OAP leads to more mathematically demanding problems (also NP hard). In general, MRTA is not a one-time assignment and becomes a dynamic decision problem, since utilities may vary or tasks can terminate or be created. The static assignment can not be longer considered applicable and iterative procedures must instead be sought [12], [13].

A key feature for the MRTA policies is if they work in a centralised or distributed way. In centralised approaches, all the information is communicated to a central entity (a server) that usually calculates the optimal allocation. The strong point of these approaches is that they can use the best known algorithms and usually have more information available than distributed or local algorithms [14]. A centralised planner can in theory compute the optimal allocation. In practical situations, where communication is not perfect and reliable, distributed approaches are required.

Several approaches aimed to decentralise existing classical approaches have been proposed in the robotics community [9], [10], [14]. In general, they provide sub-optimal solutions, but they can handle poor communication and require reduced computational burden.

Stochastic models such as collaborative or adversarial stochastic frameworks [10], [14] can be used to provide an optimal control strategy in tightly-coupled domains. Drawbacks of these models are, however, numerous: they

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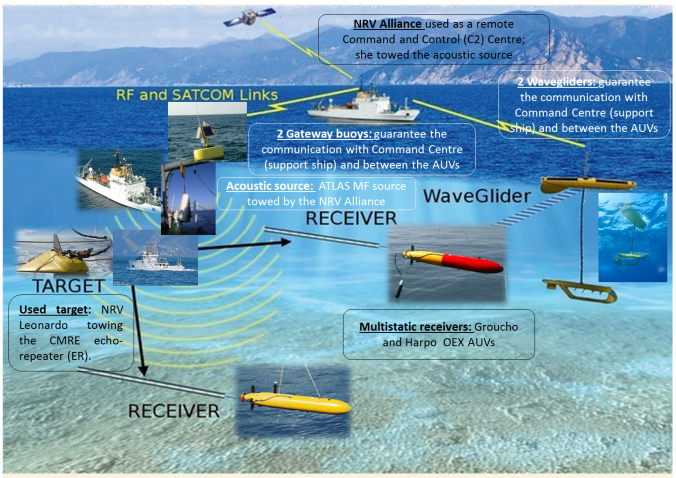


Fig. 1. CMRE cooperative ASW multi-static network as deployed during LCAS15 trial.

are computationally expensive and include some degree of centralisation to compute joint policies.

Behavioural approaches can provide ad hoc solutions for MRTA, such as the ALLIANCE architecture solution proposed in [15], which represents one of the earliest demonstrations of iterated assignment architectures to multi-robot task allocation [9]. These approaches, while easy to implement in a robotic team, generally lack a detailed evaluation of the optimality of the solutions found.

A task allocation algorithm can be seen as a method to distribute common resources among the team members. Inspiration can be drawn from the human market economies, in which the individual pursuit of profit leads to the redistribution of resources and to an efficient production of output [16]. This idea originated a family of strategies popular in robotics, the auction/market based schemes.

In this virtual economy robots are traders, tasks are traded as commodities and virtual money acts as currency. Robots compete to get assigned to a task by participating in auctions which produce efficient distributions based on preferences. When the system is correctly designed, each robot acts to maximise its own profit and this action improves the group efficiency. This is the core of the *market-based* approaches: the design of the costs, revenues and auctions mechanisms in such a way that the pursuit of individual profit leads to globally efficient solutions.

In the so-called auction-based algorithms, bids are based only on estimated costs [12]. More in general, when bids involve costs and rewards we talk of market-based approaches. Auction/marked based schemes, in general distributed, have been applied in several scenarios [10], [13], [16], [17] and can have also centralised elements (e.g. the leaders concept as in [17]), residing in the middle of the spectrum between centralised and distributed approaches. These methods have gained popularity in the robotics community.

We underline that the limitations of underwater communication (unreliability, low range and low bandwidth) [18] make MRTA challenging in an underwater scenario and make a centralised approach not feasible. This adds to the engineering difficulties in deploying and managing teams of vehicles. For these reasons, examples of experiments at sea in which multi-robot coordination is demonstrated are rare. Only a few examples are present in which groups of robots are coordinated in formation [19] and in which a team of gliders is controlled in adaptive sensing missions [20]. Task allocation schemes in complex underwater multi-robot systems are usually tested in simulation environments [1], [21]–[23], in general without the required emphasis on the role of communication in the performance of the adopted algorithms.

In this paper, we propose the PADA (Periodic Auctions Distributed Algorithm) as a viable solution to MRTA for an underwater surveillance robotic network. PADA works by using negotiations among neighbouring nodes and requires only local communications. The task allocation is solved through periodic auctions. In each auction, a node bids in a virtual market to be assigned to the task it is best suited to. Particular attention has been paid to make the auction scheme robust to intermittent communications. In our scenario, we consider continuous tasks (i.e. tasks which do not terminate) consisting in surveillance of areas for detecting possible intruder targets. An ASW network, similar to CMRE's, is considered as a case study to demonstrate our approach.

## II. Area Surveillance Task

We consider the team's mission composed of area surveillance tasks. The AUVs are requested to survey some areas respecting some time constraints. The vehicles have to sense the area of interest periodically with their sensor (the towed hydrophone array) due to the dynamic nature of the problem (the possible intruder moves).

Each task $t_i$ is associated with a geographical area $A_i$ and a racetrack path which the robots cover when allocated to $t_i$. More optimised paths could be adopted to cover the region, nevertheless a simple track is used for a better evaluation of the MRTA. We allow that more than one robot can be assigned to the same task. This violates the assumption of the classical OAP and makes our problem more difficult.

### A. Coverage index

A coverage index for $A_i$ is built based on the cumulative probability of detection on the patrolled area, computed over a moving, relatively narrow, temporal window. High values of this quantity imply that a target, if present, will likely be detected, potentially leading to successful target tracking and classification.

The robots sense the environment according to a probabilistic sensor model. It is assumed that all the sensor measurements are temporally and spatially independent. A patrolled area $A_i$ is discretised into cells. The computed cumulative probability of detection is stored in an $X \times Y$ matrix, $\mathbf{M_k^i}$. The value $M_k^i(i,j)$ is the cumulative probability of detection of the cell $(i,j)$ at time $k$ for $A_i$. Initially, all the entries of the matrix $\mathbf{M_0^i}$ are initialised to zero. Then, as the the robots scan the area with their sensors, the matrix is updated according the following procedure:

$$M_k^i(i,j) = \begin{cases} 1-(1-M_{k-1}^i(i,j))\prod_s(1-p_s(\mathbf{r_s},\beta_s)) \\ \quad \text{if } (i,j)\in D(\mathbf{x_s},\psi_s) \\ M_{k-1}^i \quad \text{otherwise} \end{cases} \tag{1}$$

where the product is over the number of robots assigned to the area under consideration, and $p_s(\mathbf{r},\beta_s)$ is the probability of detection of robot $r_s$ for the cell $(i,j)$. This depends on the distance $\mathbf{r_s}$ and bearing angle $\beta_s$ of the cell with respect to the position of $r_s$, that is $\mathbf{x_s}$, and its heading angle, $\psi_s$. The cell $(i,j)$ is updated only if it is in $D(\mathbf{x_s},\psi_s)$, the sensor footprint. $\mathbf{M_k^i}$ is computed considering a moving time window of length $L$. That is, by iteratively using (1) from time indices $k-L-1$ to $k$.

$\mathbf{M_k^i}$ is the probability that at least one of the sensors detects a target (if present) in the area $A_i$ at least once in the last $L$ scans. This takes into account the dynamic nature of the problem: since the target can move, we only trust recent measurements.

To define the task utility we need to express the coverage through a single number. We define a matrix $\mathbf{H^i}$ of dimensions $X\times Y$ representing the *objective* cumulative probability of detection over all the cells of the area. $\mathbf{H^i}$ is the goal to be reached set by the mission designer. We can now compute an index $\alpha^i$, which is a measure of how much the set objective has been met by the sensing assets. At a certain time $k$, we compute $\alpha^i$ as:

$$\alpha^i = \sum_{i,j}\varphi_{i,j}^i \quad \text{with} \quad \begin{cases} \varphi_{i,j}^i = H^i(i,j) - M_k^i(i,j) \\ \text{if } \; H^i(i,j) - M_k^i(i,j) > 0 \\ \qquad \varphi_{i,j}^i = 0 \\ \text{if } \; H^i(i,j) - M_k^i(i,j) \le 0 \end{cases} \tag{2}$$

The method is inspired by the *sampling on-demand* paradigm proposed in [24]. The $\mathbf{H^i}$ matrix allows the definition of requirements in terms of the quality of the survey, and provides a way to vary the objective coverage over the different sub-regions of the area $A_i$, since some areas can be more important to patrol than others. The computed number $\alpha^i$ describes concisely how well the area $A_i$ has been surveyed. The lower $\alpha^i$ is (0 if the goal is fully reached), the more the set objective has been achieved.

*Urgency factor*

An urgency factor, $I^i(t)$, is introduced to quantify how urgently $A_i$ needs to be surveyed. $I^i(t)$ is initialised to 1. It increases over time if $\alpha^i$ is larger than a certain pre-fixed threshold $\eta$, meaning the area is not adequately covered. $I^i(t)$ is computed as:

$$I^i(t) = \delta + (1-\delta)\lambda(t-t_0)^{(t-t_0)} \tag{3}$$

where $t_0$ is the time from which the increase of the urgency factor has started, $\lambda$ is a value function of $(t-t_0)$ to shape the increase of $I^i(t)$ with time. As the time increases, and the area is not adequately surveyed, $I^i(t)$ gets larger up to the maximum value equal to $\delta$.

$t_0$ is modified on the basis of how the patrolling is proceeding. If $\alpha^i$ becomes lower than $\eta$, $t_0$ is increased and causes a reduction of $I^i(t)$. The process guarantees that $I^i(t)$ comes back to the value of 1 only if $\alpha^i \le \eta$ for a certain time.

The urgency factor increases the importance to survey an area if the survey objectives have not been achieved. To lower $I^i(t)$, the team has to patrol the area adequately, reaching the mission objectives for a certain amount of time.

*Surveillance task utility*

We are now able to write the task utility $u_{ki}$, for a robot $k$ to perform a task $i$. This utility, computed by each robot, is used in the auction-based MRTA algorithm. For $t_i$, with the associated area $A_i$, we compute the utility as:

$$u_k^i = w_k^i - c_k^i \tag{4}$$

$w_k^i$ being the reward to accomplish the task as computed by $r_k$ and $c_k^i$ the cost associated to $r_k$ to reach the racetrack associated to $t_i$. $w_k^i$ is the reward the robot would have to be assigned to the task. This quantity drives the robots to decide on which task to bid. $w_k^i$ is defined as:

$$w_k^i = \alpha_k^i \frac{N_i}{N_{max}} I_k^i(t) \tag{5}$$

with $\alpha_k^i$ the current coverage index of $A_i$ as computed in (2) by $r_k$ with its knowledge of the other robot actions, $N_i$ is a measure of the dimensions of the area $A_i$ and $N_{max}$ a measure of the largest area in the tasks to allocate. $I_k^i(t)$ is the urgency index for $t_i$ as computed in (3) by $r_k$.

The cost $c_k^i$ is a scaled distance from the current position of the $r_k$ to the closest point of the racetrack associated to $A_i$ and gives a measure of how difficult it is for the robot to reach the area.

## III. Problem definition

In our scenario we assume a set of $n$ robots (denoted $r_1,\ldots,r_n$) and a set $T$ of $m$ tasks, denoted $t_1,\ldots,t_m$. We have to determine distributed control laws that partition the robots into $m$ groups of size $l_k$ associated to each task, $t_k$, with $k=1,\ldots,m$. The tasks considered are the surveillance tasks previously described. We also make the assumption that one robot senses only the area related to the task to which is currently allocated.

The proposed problem can be formulated as to find $mn$ non-negative integers $\gamma_{ij}$ (which must be either 0 or 1, 1 meaning that $r_i$ is assigned to $t_j$), that minimise the following group objective function $J$:

$$J = \sum_{i=1}^m w_i + \beta\sum_{j=1}^n c_j \tag{6}$$

where $w_i$ is the reward related to $t_i$ computed by considering the measurements of all the team robots, $\beta$ is a weight factor and $c_j$ is the cost of $r_j$ relative to the task which is currently assigned to. The minimisation being subject to:

$$\sum_j^n \gamma_{ij} = 1, \quad 1 \leq i \leq m$$
$$\sum_i^m \gamma_{ij} \leq l_j, \quad 1 \leq j \leq n \tag{7}$$

Our problem is more complex than the OAP previously described for several reasons. The first constraint of (7) is present also in the OAP. It states that one robot can be allocated to only one task. The second one, otherwise, allows that up to $l_j$ robots can be assigned to $t_j$. This defines the problem as a Multi-Robot Task (MR) problem [9], [10]. This is known in the multi-agent community as a coalition formation problem which in its most general form is intractable [9] and which has received a significant amount of interest in the multi-robot coordination literature [10].

To minimise the group utility in (6) the group members must survey the areas $A_i$s (reducing $w_i$s) respecting the required time constraints (dictated by the urgency factor $I^i(t)$ - see (5)). At the same time, the robots must reduce $c_j$s, their cost on the currently assigned task. This implies to reduce the number of switching from one area to another which is the main cause of the increase of $c_j$s. One robot decides to change the area to survey considering its reward and the cost to reach that area: a trade-off needs to be reached by the group between task switching and surveying the areas with highest rewards.

We underline that the robots during the MRTA use approximate information due to the limitations in communication. They compute their coverage cognitive map $\widehat{\mathbf{M}}^{\mathbf{i}}_{\mathbf{k}}$ for each $A_i$ which is an approximation of the real $\mathbf{M}^{\mathbf{i}}_{\mathbf{k}}$. With the used type of task, the computation of $\mathbf{M}^{\mathbf{i}}_{\mathbf{k}}$ requires information from the other assets (i.e. their sensing location during the navigation). The utilities of tasks are therefore influenced by the actions of other assets incurring in cross-schedule dependencies [10]. The utility of a robot for a task depends also on the schedules of other robots in the system.

### A. The Periodic Auctions Distributed Algorithm (PADA)

We propose a distributed market-based MRTA algorithm, the Periodic Auctions Distributed Algorithm (PADA), in which robots bid periodically for task allocations. We make the assumption that each robot has knowledge of all the tasks present in the system and of the maximum number of robots which can be allocated to each task. PADA offers a distributed approximation to (6) and (7) to be implemented on underwater vehicles. There is no presence of a central auctioneer which could be a problem in limited communication environments. In our framework, any robot becomes an auctioneer when it plans to execute a task. Each robot estimates, based on its local knowledge of the tactical scene, the utilities of the tasks and selects the one which it wishes to be assigned to. Then, the robot bids for that task. Periodically, each robot evaluates the bids received for the task for which it is bidding for and a winner of the auction is awarded (the agent with the highest bid). The robots which are not the winners of the auction select another task to bid for and start other negotiations. The assignment process consists in a sequence of such auctions taking place locally among the robots which can communicate with each other. The auctions are periodic to deal with unreliable communications. When new information from some bidders is available, it is taken into account in the current negotiation.

The task assignment is performed considering the status and knowledge of the world attainable at the assignment time (Instantaneous Assignment (IA) according to the taxonomy in [9], [10]). Any situation unknown at the negotiation time is not taken into account. However, PADA introduces means to allow renegotiations (task reallocations) to reallocate dynamically tasks inside the team to better achieve the group's objective. This is necessary to manage continuous tasks which do not terminate. This also handles other events such as changes in the number of team members, creation of new tasks or with required changes in the allocation due to the changing tactical scene (some tasks may become more important than others). PADA takes into account the need to limit the task switching, which reallocation may imply. A trade-off between the need to survey high reward areas and reduce the task switching events is sought to improve the team performance.

The same algorithm runs on each robot. We report in Algorithm 1 the pseudocode running on $r_i$. Every robot starts its mission selecting a task to bid for. That task becomes the task in execution and the robot starts to accomplish it. In our case, it moves towards the relative racetrack. This facilitates also the auction process: robots bidding for the same task will head towards the same area. Getting closer increases the probabilities of successful communications leading to the resolution of the auction.

Acoustic messages are exchanged between the robots. We assume that the messages contain the status of the AUVs (e.g. the position, heading and speed) and information about the task allocation. This includes the task $t_j$ for which the robot $k$ is bidding for, the bid value $b^j_k$ and the urgency factor at the time of message creation, $T_c$, of the task $t_j$ as computed by $r_k$, that is $I^j_k(T_c)$. The information is kept minimal to make feasible the porting of the algorithm to the underwater scenario. More complex communication strategies (which would increase the bandwidth required) can also be considered. For instance one robot could broadcast information about the other robots previously received.

If messages from other robots are received, the Allocation Table structure $A^i_T$ is updated. $A^i_T$ contains all the information which $r_i$ has regarding the other vehicles and the knowledge about their allocation to the tasks. The function `UpdateAllocationTable` stores the allocation of a certain robot to the task in execution (the task the robot is bidding for), $\{r_k, t_j\}$.
`UpdateUrgencyFactors` updates the urgency factors $I^i_k(t)$ for each task $t_i$ present in the system with the minimum of the received values from other assets bidding for task $t_i$, only if the minimum value is lower than the stored one. A received $I^i_j(t)$ lower than the current one means that the remote asset has more information regarding the execution of $t_i$. The exchange of $I^i(t)$ is a concise way

**Algorithm 1:** PADA algorithm for $r_i$.

```
if IsMsgPresent()=true then
    UpdateAllocationTable() ;
    UpdateUrgencyFactors() ;
    StorePositionAssets() ;
end
if IsPingTime()=true then
    ComputePositionAssets();
    ComputeTaskUtilities();
end
if IsAuctionResolutionTime()=true then
    [isWonAuction,isToCheckTaskReallocation]=ResolveAuction() ; // described in Algorithm 2
end
[t_j]=SelectOneTaskToExecute(isWonAuction,isToCheckTaskReallocation);
ProduceMsg(t_j);
UpdateWinnerTable();
UpdateAllocationTable();
with IsMsgPresent returns true if any message has been received from other assets;
IsPingTime returns true if it is time at which a ping has been performed;
IsAuctionResolutionTime returns true if it is time to resolve an auction;
isWonAuction being a flag stating the results of an auction;
isToCheckTaskReallocation being a flag commanding to check a possible task reallocation;
ProduceMsg(t_j) function producing an acoustic message to be sent to collaborators;
```

to share information about the task execution state. Finally, `StorePositionAssets` writes in $A_T^i$ the information about the positions of the assets.

At each ping time, the robot estimates the positions of the other vehicles, based on the received information and assuming constant velocity (`ComputePositionAssets`). The utilities of all the tasks are then computed (`ComputeTaskUtilities`) using the extrapolated positions/heading of the vehicles (their measurement locations).

Periodically, every robot resolves an auction by the `ResolveAuction` function. The period with which the auctions are resolved is set large enough to guarantee the possibility for each robot to receive a bid from neighbours on the current task in execution. The `ResolveAuction` algorithm is described in detail in Algorithm 2. The bid of $r_i$ for $t_j$, $b_i^j$ is computed as $-c_i^j$, with $c_i^j$ being the scaled distance from the position of $r_i$ to the closest point of the racetrack associated to $t_j$. We consider $-c_i^j$ since the rewards of the tasks have the same value from a group objective perspective (that is if we have knowledge of all the team's measurements), even if they may have different values if computed locally on-board each robot. The only part that changes in the bids is therefore the cost. The robot evaluates all the bids received during the current auction time window for the task $t_j$ in execution on $r_i$. If no bids are present (only $r_i$ is bidding on the task), $r_i$ assumes to be the winner of the auction, but returns *isToCheckTaskReallocation*=1, to command a possible task reallocation. In the case there are some bids received from other nodes, all the bids placed by the past winners on auctions on $t_j$ are removed from this set. $r_i$ then assumes to be the winner of the auction if:

- no other bids are present;
- $r_i$ has bidden equal to the highest received bid and $i$ is a value larger than the id of the highest bidder robot;
- $r_i$ has bidden higher than the highest received bid.

Otherwise it assumes to have lost the negotiation and stores the id of the winner of the auction in $W_i^j$. The winners will not be considered as participant in future auctions by $r_i$ for a certain time. This is to handle with imperfect (intermittent) communication and avoid contrasting results in the auction. An asset that wins the auction once, will be assumed as the winner in the near future.

The robot then selects one task to execute, considering the results of the auction by the `SelectOneTaskToExecute` function which works as follows. Let us define the set of available tasks as computed by $r_i$ at time $t$ as $T_i^a(t) = \{t_k \in T | \chi_k(t) > 0\}$ with $\chi_k(t)$ being the number of robots which can still be assigned to $t_k$ at time $t$, given the maximum number of allocatable robots $l_k$ and the current known assigned agents. If no task is currently under execution on the robot, the highest utility task $t_j \in T_i^a(t)$ is selected. If an auction is won on $t_j$, $t_j$ continues to be the task in execution, unless the bid of $r_i$ was the only one on $t_j$ (*isToCheckTaskReallocation*=1) (no other bids are received from other agents). In this case, we select the task $t_k \in T_i^a(t)$ with the highest utility $u_i^k$ (which may be different from $t_j$). If the highest utility task $t_k$ is different from the task currently in execution $t_j$, we select it only if its utility $u_i^k > u_i^j + \eta_r$, with $\eta_r$ being a reallocation threshold. This mechanism gives the opportunity to a robot which is the only one assigned to a certain $t_j$ to evaluate a possible reallocation

**Algorithm 2:** PADA auction resolution for $r_i$. This algorithm is executed by *ResolveAuction* function in Algorithm 1.

**Input:** a task $t_j$ selected to bid for and a bid for it $b_j^i$; current time $T_C$
**Output:** $isWonAuction$, $isToCheckTaskReallocation$

Set $isWonAuction = 0$, $isToCheckTaskReallocation = 0$;
Retrieve the received bids of the robots bidding for $t_j$ in the last auction time window. That is the set $B_j = \{b_k^j | t_b(r_k) = j\}$, with $t_b(r_j)$ being a function which returns for $r_j$ the task which is bidding for;
Retrieve the previous robots winners in auctions for $t_j$ as known to $r_i$, that is the set $W_i^j = \{r_k \| r_k$ has been awarded as winner of an auction on $t_j$ by the current vehicle$\}$;
**if** $B_j = \emptyset$ **then** `// only` $r_i$ `is bidding for` $t_j$`; we consider possible task reallocation`
    $isWonAuction = 1$;
    $isToCheckTaskReallocation = 1$;
**end**
Remove from the set $B_j$ the bids of the robots which are previous *winners* on auctions on the task $t_j$, that is $\{r_k \| r_k \in W_i^j\}$;
**if** $B_j = \emptyset$ **then**
    $isWonAuction = 1$;
**else**
    **if** $b_i^j$ =`MaxBid(`$B_j$`)` **then** `//` $r_i$`'s bid has the same value as the highest value of the received bids: the robot with the highest id value wins the auction`
        **if** $i >$`MaxBidId(`$B_j$`)` **then**
            $isWonAuction = 1$;
        **else**
            $isWonAuction = 0$;
            `AddWinner(MaxBidId(`$B_j$`),`$t_j$`,` $T_C$`);`
        **end**
    **end**
    **if** $b_i^j >$`MaxBid(`$B_j$`)` **then** `//` $r_i$ `has won an auction with other participants`
        $isWonAuction = 1$;
    **end**
    **if** $b_i^j <$`MaxBid(`$B_j$`)` **then** `//` $r_i$ `has lost an auction with other participants`
        $isWonAuction = 0$;
        `AddWinner(MaxBidId(`$B_j$`),`$t_j$`,` $T_C$`);`
    **end**
**end**
**return** *isWonAuction*;
**return** *isToCheckTaskReallocation*;
with `MaxBid(`$B_j$`)` returns the maximum bid $b_m^j$ of $B_j$ or 0 if $B_j = \emptyset$;
`MaxBidId(`$B_j$`)` returns the id of the robot which made the maximum bid;
`AddWinner(`$k$`,`$t_j$`,`$T_C$`)` adds to the set of winners for $t_j$, $W_i^j$, the robot of id $k$ at time $T_C$;

strategy and to switch to other tasks. In the case an auction is lost, the robot selects another task following the same procedure as in the previous case. The robot excludes for the selection of a new task to bid for those tasks $t_k$ which it knows being already in execution on a number of robots $\geq l_k$.

The acoustic message with the new bid can then be created (`ProduceMsg`). The structure containing the winners for all the tasks, $W_i$, is then updated, removing, for each task, the robots which have not resulted winners in auctions on that task for a certain amount of time (`UpdateWinnerTable`). A robot is also removed as assigned to a task from the allocation table $A_T^i$ if no information has been received about that assignment for some time (`UpdateAllocationTable`). This allows to negotiate again a task after some time to better adapt the general team allocation as the tactical scenario evolves.

Given $n$ robots, each implementing the PADA algorithm, the team is always guaranteed to reach a feasible assignment which respects the availability of the tasks. Assuming perfect

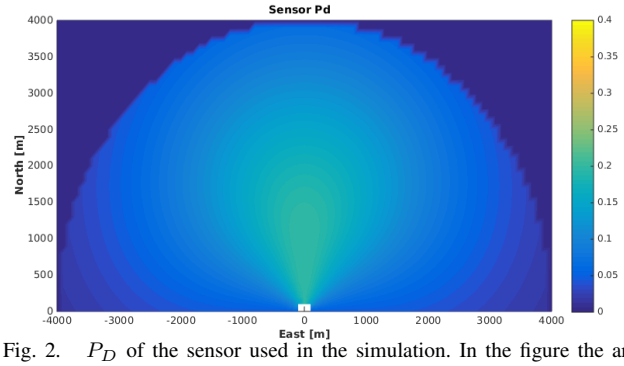


Fig. 2. $P_D$ of the sensor used in the simulation. In the figure the array towed by the vehicle is oriented west-east and located at (0,0) location. $P_D$ is highest at broadside and decreases with the increase of distance from the array.

communication, the algorithm reaches a feasible assignment after $n$ auctions, in the worst case scenario. Assume $n$ tasks with each one having $l_i = 1$. Without loss of generality, we consider that the $n$ robots start bidding for the first task. The PADA algorithm assumes that one of the robot is recognised by the team as the winner at each auction. The remaining $n-1$ robots bid for the second task and a new winner is declared. Proceeding in this way, after $n$ auctions each robot is assigned to one task.

### B. Results

Simulations have been carried out to evaluate the algorithm's performance and to study how changes to its parameters can influence the robots behaviours. In particular, we were interested in studying the effects of how a decrease in the quality of communication impacts on the performance. We report results from three different scenarios. In each of them 3 robots are used and start their mission from the same location.

Two tasks are provided to the team: $t_1$ related to an area to patrol, $A_1$, located in the north part of the operative area and $t_2$ related to the area $A_2$ positioned at west. Both tasks have the same parameters regarding the coverage index and the urgency factor, but $A_1$ is larger than $A_2$. This implies more observations of $A_1$ are needed to achieve the survey objective. Each area is associated with a racetrack (a rectangular path composed of 4 waypoints). The racetracks associated to $A_1$ and $A_2$ can be seen in Fig. 4. The robot, after deciding to execute a task, moves towards the associated racetrack and then covers the path repeatedly until the task in execution is changed. Each task $t_k$, is characterised by $l_k = 2$: a maximum of 2 vehicles can be simultaneously allocated. To model the real underwater scenario, communication is managed through a Time Division Multiple Access (TDMA) [18] scheme (as used in CMRE ASW network). At teach TDMA slot, a robot transmits one message for negotiating the task allocation.

In Tab. I we report the most important parameters used in the presented simulations.

Each robot uses the sensor model shown in Fig. 2, where the probability of detection $P_D$ is shown as function of the bearing angle and range. The used model captures the features of monostatic measurements with the towed array:

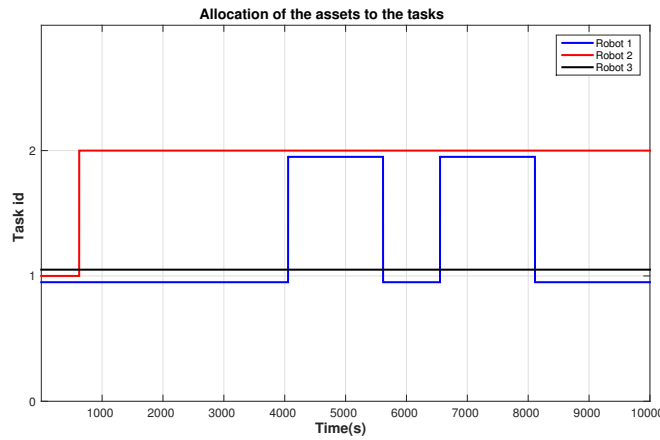


Fig. 3. Scenario 1 (perfect communication) - task allocation of the robots.

the highest $P_D$ is at array's broadside and decreases with the increase of distance from the array. We also assume that one robot senses only the area related to the task to which is currently allocated.

Each scenario is characterised by different communication performance:

- Scenario 1 - perfect communications.
- Scenario 2 - 40% of message transmission success rate up to 2 km of range between the communicating assets. Then the success rate decreases linearly up to 10% at a 4 km range.
- Scenario 3 - 10% of success rate on every sent message.

The perfect communication case allows us to study the behaviour of the algorithm without the influence of not received messages. The robot-to-task allocations during one typical mission of scenario 1 are shown in Fig. 3.

The three robots select $t_1$ as the task to execute at the beginning of the mission since no communication has occurred yet between the assets. The decision on $t_1$ is dictated by the combined effect of the larger reward relative to the larger area of $A_1$ and to the proximity of the nodes to it (lower penalty $c_k^i$). They start heading towards $A_1$ and begin transmitting bids for $t_1$. The first auction is resolved with $r_1$ as the winner (the closest robot to $A_1$). In the next one $RX_3$ is recognised as winner, so $r_2$ selects $t_2$ and starts moving towards $A_2$ (see Fig. 4).

The mission proceeds with two assets ($r_1$ and $r_3$) allocated to $t_1$ and one ($r_2$) to $t_2$. While the urgency factor for $t_1$ remains equal to 1 since the two robots succeed in achieving the mission objectives in terms of area coverage, the urgency factor for $t_2$ increases. $r_2$ alone, in fact, is not able to accomplish the mission requirements set for the coverage of $A_2$.

This leads to the decision of $r_1$ to switch tasks and move towards $A_2$. As can be seen in Fig. 3, this happens twice during the overall mission. The group objective function to minimise is reported in Fig. 5 while the reward and urgency factors for the two tasks are shown in Fig. 6. The decision of $r_1$ to survey $A_2$ is driven by the increase of the urgency factor (which results also in an increase of the group objective function). $r_1$ covers $A_2$ and then comes back to help $r_2$ in

TABLE I

PARAMETERS USED FOR THE SIMULATIONS.

| Parameter | Value | Notes |
|---|---|---|
| *Parameters related to the assets* | | |
| Number of assets | 3 | |
| Robot speed [m/s] | 1 | |
| PRI [s] | 24 | Pulse Repetition Interval |
| *Parameters related to the acoustic communications* | | |
| Time-slot for each asset [s] | 13 | 7 s to send messages |
| TDMA frame length [s] | 39 | |
| *Parameters related to the auction* | | |
| Auction resolution period [s] | 312 | period with which auctions are solved. 8 TDMA frames |
| *Parameters related to the tasks* | | |
| Number of tasks | 2 | |
| $l_k$ | 2 | Maximum number of vehicles which can be assigned to $t_k$ (the same for every task) |
| $H(i,j)$ | 0.9 | Objective value of the cumulative probability over each cell |
| length of the moving window to compute $\alpha$[s] | 144 | 6 PRIs |
| $\delta$ | 10 | $\delta$ value for the urgency factor (reached after 1.3 hours) |
| percentageReset | 0.35 | percentage of the initial reward of the task causing the decrement of the urgency factor |

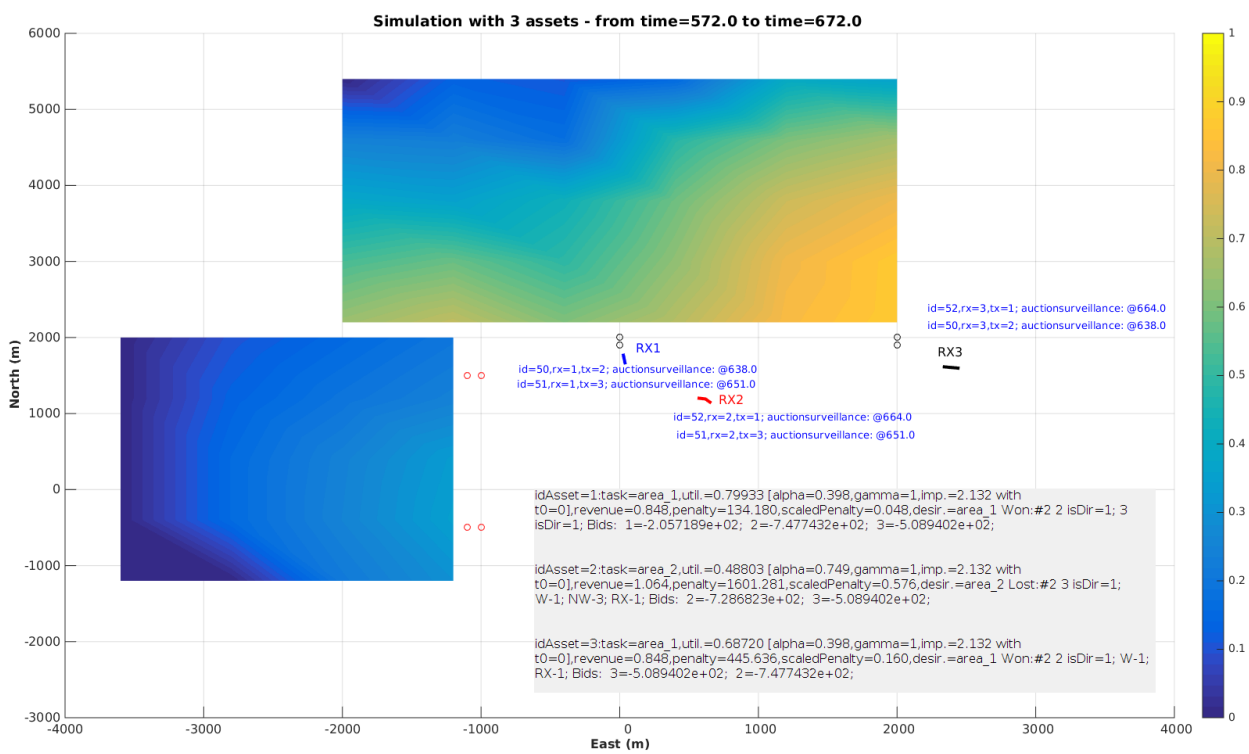


Fig. 4. Scenario 1 - situation of the assets at mission time 672 s. The robots are indicated as $RX_1$, $RX_2$ and $RX_3$. The colours on each patrolled area are the computed cumulative $P_D$ by considering all the measurements of the sensors assigned to that specific area. The text in blue shows the successfully received acoustic messages, with the id of the transmitting asset shown. The two racetracks are also indicated by circles (the waypoints constituting the racetrack) nearby $A_1$ and $A_2$. Robot 2 is moving to $A_2$ after Robot 1 and Robot 2 have won auctions to survey the highest reward area, $A_1$.

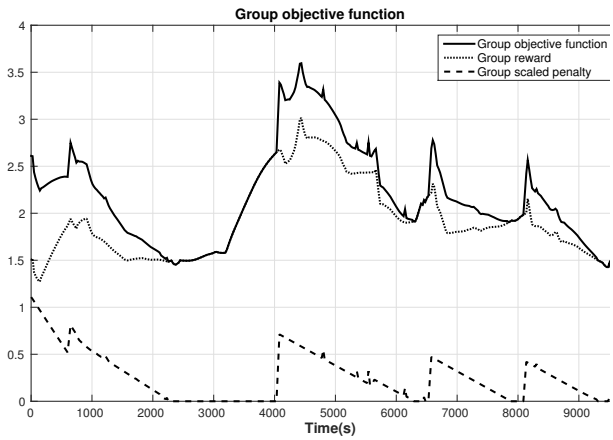


Fig. 5. Scenario 1 (perfect communication) - team utility, team reward ar team penalty.

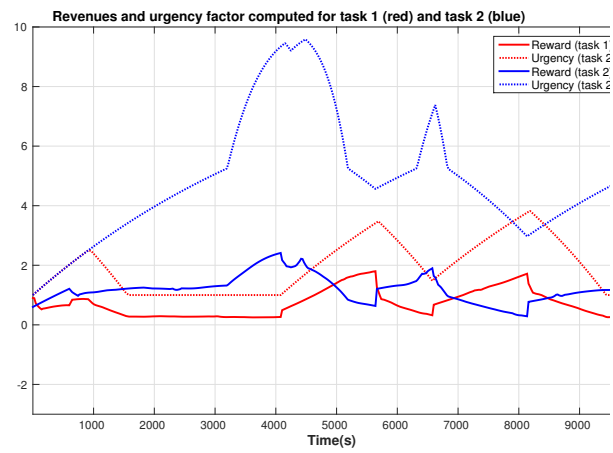


Fig. 6. Scenario 1 - reward and urgency factors for $t_1$ and $t_2$ computed by considering all the measurements of the robots assigned to the tasks.

guaranteeing an adequate coverage of the largest area $A_1$.

In Scenario 2, the communication quality decreases. Nevertheless, the algorithm behaves in a quite similar way, showing robustness to intermittent communication. Evaluating the bids over a temporal length gives the robots more possibilities to receive information from collaborators to resolve auctions in an appropriate way.

Finally, scenario 3 is the most difficult since the success rate for receiving messages is low (10%). The low transmission success rate impacts on the task allocation algorithm (see Fig. 7 causing more task switches which lead to undesired transits from one area to the other. The group objective function in this case is reported in Fig. 8.

To quantify the performance in the three cases we compute the maximum and mean value of two fundamental quantities: the group objective function $J$ and its reward part, that is $\sum_{i=1}^{m} w_i$, being the sum over all the tasks. The quantities are reported in Tab. II, as the average values over 10 simulation runs for each scenarios. It is evident from the results that, from a group objective function perspective, the results are very similar in scenario 1 and scenario 2. This demonstrates the robustness of the algorithm to the deterioration of communication performance. In scenario 3, instead, the

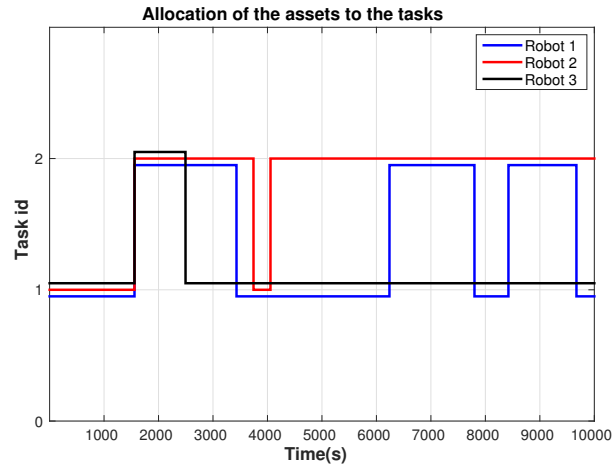


Fig. 7. Scenario 3 - task allocation of the robots.

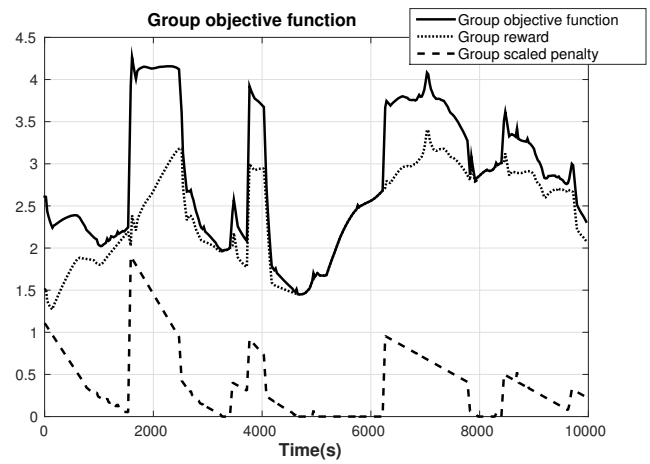


Fig. 8. Scenario 3 - team utility, team reward and team penalty.

allocation performance decreases due to the increase of task reallocations. The higher number of robot transits between the two areas reduces the quality of the coverage (higher reward part of $J$) and increases the penalties. These two combined factors cause an increase in the $J$ function.

## IV. Conclusion

We have investigated the task allocation problem for a team of underwater robots, focusing on a robotic network for an ASW application. Task allocation becomes central to improve the team overall performance.In our scenario the severe limitations of acoustic communication make task allocation challenging.

We proposed a market-based approach as a viable solution for task allocation. The method works in a completely distributed fashion and, through periodic auctions, solves the dynamic assignment of robots to tasks. The algorithm relies on negotiations among neighbouring nodes and requires only local communication, with no need for a central auctioneer. The algorithm can work with several types of tasks once their utility is defined. In our work continuous tasks (i.e. they never terminate) are considered. They consist in the surveillance of areas of interest, which must be periodically surveyed. More than one robot can be allocated to each task, to enable cooperative survey of the region. However

TABLE II

RESULTS OF THE ALGORITHM IN THE THREE SCENARIOS. AVERAGE VALUES ON 10 SIMULATION RUNS PER SCENARIO.

| Parameter | Value |
|---|---|
| *Scenario 1* | |
| $max(J)$ | 3.59 |
| $mean(J)$ | 2.15 |
| $max(\sum_{i=1}^{m} w_i)$ | 3.01 |
| $mean(\sum_{i=1}^{m} w_i)$ | 1.9 |
| *Scenario 2* | |
| $max(J)$ | 3.81 |
| $mean(J)$ | 2.2536 |
| $max(\sum_{i=1}^{m} w_i)$ | 3.23 |
| $mean(\sum_{i=1}^{m} w_i)$ | 1.99 |
| *Scenario 3* | |
| $max(J)$ | 4.26 |
| $mean(J)$ | 3.40 |
| $max(\sum_{i=1}^{m} w_i)$ | 2.39 |
| $mean(\sum_{i=1}^{m} w_i)$ | 2.81 |

this possibility increases the mathematical difficulty of the assignment problem making it a coalition formation problem [9]. Particular attention is paid to make the auction scheme robust to intermittent communication. The algorithm waits for messages for several communication frames before making a decision. Furthermore, the task allocation policy explicitly takes into account task reallocations to better adapt to the evolving conditions. A trade-off is sought between the reduction of the the team rewards (assigning more robots to survey not adequately patrolled areas) and avoiding frequent task reallocations, which cause transits of robots from one area to another.

The proposed algorithm were tested in simulation in a Matlab framework. Three scenarios with different communication performance were presented. Results show that the algorithm is able to coordinate the robots to optimise the team objective function of interest. The algorithm proves robust to the communication degradation and maintains acceptable performance even as the number of switches between the tasks increases. The periodic auctions policy allows the robots to renegotiate the tasks through the mission. This handles possible lost messages, giving more opportunities to the nodes to participate in the auction.

In future work we will continue the analysis of the algorithm's performance in poor communication conditions. Additional tasks will also be added into the pool of possible tasks to expand the network capabilities and better represent a real ASW mission.

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*Title*

A market-based task allocation framework for autonomous underwater surveillance networks

*Abstract*

Realisation of underwater robotic surveillance networks raises several challenges for marine robotics. The underwater scenario is typically characterised by intermittent and unreliable communication. This makes it challenging to develop task allocation schemes suited to work effectively in underwater surveillance applications. We propose a market-based approach to task allocation, which works in a completely distributed way. Through periodic auctions, the algorithm achieves the dynamic assignment of robots to tasks throughout the mission. There is no central auctioneer and any robot becomes an auctioneer when it intends to execute a task. Through periodic auctions, all the robots are sequentially allocated to the tasks. The algorithm is designed to increase the robustness to poor communication and to allow task reallocation, to adapt the allocation to the evolving scenario. Results from computer simulations are reported that support the proposed approach. An Anti-Submarine Warfare application is considered to test the scheme. In this application, the surveillance of areas of different dimensions has to be accomplished by a team of AUVs.

*Keywords*

Resource management, robot sensing systems, surveillance, robot kinematics

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