Cooperative-Adaptive Algorithms for Targets Localization in Underwater Environment

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Abstract—Underwater target localization using several AUVs (Autonomous Underwater Vehicles) is a difficult issue. A systematic and exhaustive coverage strategy is not efficient in term of exploration time: it can be improved by making the AUVs share their information and cooperate to optimize their motions, dealing with the environmental changes and reducing the amount of redundant data. The contribution of this paper is the definition of such a strategy that adapts each vehicle motions according to its or others’ sensory information. Communication points are required to make underwater vehicles exchange information: for that purpose the system involves one ASV (Autonomous Surface Vehicle), that helps the AUVs re-localize and exchange data, and two AUVs that adapt their strategy according to gathered information, while satisfying the associated communication constraints. In order to test our algorithms we extend an existing architecture to account for the information gathered and exchanged by the AUVs.

I. INTRODUCTION

A. Problem description

The problem of exploring an unknown area is a central issue in mobile robotics. In general, the coverage of the entire terrain is required. However, this is not practical due to the resource cost (e.g. energy and execution time of the mission). This resource constraint creates an important issue in designing an exploration strategy for an underwater vehicle: how do the underwater vehicles decide where to explore next? In this paper we present an adaptive exploration strategy based on sensed data. In contrast to several exploration strategies that are non adaptive [1], our approach tries to modify the trajectory of the vehicle by maximizing the information gain to localize the maximal number of targets. In our scenario the targets are hydrothermal vents. These vents are the result of thermal and chemical output from hot spring systems in the oceans. These hydrothermal vents have attracted the scientific community for different reasons: the motion of hydrothermal sea-water through the oceanic crust influences many geological and oceanographic processes such as loss of heat from the earth, geochemical cycling of the elements, biogeochemistry of deep ocean waters and the biology of hydrothermal vents gives special features.

B. Related work using underwater vehicles

In this contribution, we want to use several underwater vehicles. When compared to a single robot, multi-robot fleets bring robustness with respect to robot failures, allow to achieve missions more efficiently (more rapidly, or with a greater spatial extent) and fulfill missions or tasks that intrinsically require the use of several robots. When it comes to information gathering missions, e.g. exploration, surveillance, target detection and localization, synergies naturally occur when robots effectively communicate to merge information gathered on the environment and to coordinate their observation plans. A large amount of work has been made in this direction in the robotics community, and the literature abounds with studies on robot fleets. In [2], the robots define their motions on the basis of the current knowledge of the target locations, and regularly broadcast their observations. Market-based approaches can be exploited to delegate goals to each vehicle [3]. Exploration of unknown areas is another problem often considered. Here, the exploration strategy is greedy, that optimize a utility / cost ratio [4], [5]. The authors [6] present a control strategy for a team of vehicles to move and rely on a gradient descent (potential field). In general, these approaches need permanent, long range and large bandwidth communications; three properties that are not satisfied for underwater vehicles. In this paper we are using several underwater vehicles that share their information. An essential difficulty of the underwater context is that acoustic communications are severely constrained, in both range and bandwidth.

Other works focused on using AUVs that are particularly suited for the detection, study and analysis of underwater phenomena. The authors in [7] proposed models for the currents and the vehicle dynamics, and exploit them to define an optimal search solution off-line. The solution is then uploaded to the vehicle, and there is no deviation caused by any on-line sensing. In [8], the authors propose a single AUV strategy to localize hydrothermal vents that adapts to the gathered data during a swathing phase: spiral paths are triggered when a chemical anomaly is detected. In the research that deal with
multiple AUVs (sometimes involving ASVs), the work of Haraksim et al. [9], [10] deal with “formations”, in which the objective is to make the vehicles follow each other, while maintaining permanent communications. In another work, the authors [11] propose an adaptive sampling strategy for a team of ASVs. The approach relies on the partition of “equal gain” areas, that are then explored by individuals. Rahimi et al. [1] propose an approach that randomly samples the environment, in a systematic way that does not take into account any sensed measure. Low et al. [12] drive the AUVs according to the sensed measures, directing the vehicles to the targets: the approach yields finer localization of targets than systematic sampling.

C. Contribution

We focus our work on the efficiency of the cooperation and exploration, which depends on the exchanged information and the duration of the data exchange. We try to minimize the data exchange range between vehicles that can reduce the exchange time and leave more time for the exploration and localization.

We use one ASV (Autonomous Surface Vehicle), that serves as a mobile baseline system for AUVs positioning and as a communication hub between AUVs. The AUVs have predefined rendezvous to exchange and re-localize themselves with the ASV.

In section II we define the used model of the target. Section III describes the building of the perceived world according to the perceived data. In section IV the used algorithms for cooperation and the amount of exchanged data are shown, and section V gives different results that are obtained using one ASV and two AUVs that explore a shared area.

II. TARGET AND SENSOR MODEL

a) Sensor model:

• Range-only sensor. This type of sensors is dedicated to define the distance to the target. For example using a sonar (sound navigation and ranging), it propagates the sound in the water to detect the contents of the water, for vehicle’s localization using LongBaseLine sonar or for fishing. The sonar according to the transmitted signal and the time taken to get back the signal, allows the vehicle to compute the distance between its position and the target/ground/fish. We can take the scenario of target localization (e.g. vent), where we know what is the maximal temperature of the target. Using a temperature sensor and according to the actual temperature measure, the vehicle can compute the distance to the target. We can model this kind or sensor with a probability density function \( P(T_{\text{sensor}}|T) \) that models its errors (e.g. a Gaussian). The overall source perception model is a convolution of the source and sensor model, the associated variations being “blurred” by the sensor model – we therefore neglect the sensor errors (all the more since most of the uncertainty comes from the model of the observed phenomenon, not from the sensor errors).

• Bearing-only sensor. This type of sensor indicates the direction of the target without knowing the distance to the target. Several types of sensor bearing exists in the literature. In our case we will use a CTD\(^1\) sensor. This sensor can measure the temperature of the place and according to the past and present value of the temperature, the vehicle can infer the target direction (we will give more details in the next section). For each sensor, its measure has an error. The temperature sensor can be modeled with a probability density function \( P(T_{\text{sensor}}|T) \) that models its errors (e.g. Gaussian).

We neglect the sensor errors (all the more since most of the uncertainty comes from the model of the observed phenomenon, not from the sensor errors).

b) Source model: The source is a vent on the seabed, emitting either clearwater, hot water, chemicals, etc. The emission expands and diffuses laterally during its ascent, which can be up to hundreds of meters,\(^2\) creating a cone shaped plume (Figure 1).

![Figure 1: Illustration of the temperature evolution within a thermal plume.](image)

We consider the case of hot sources: we discern two cases: (1) the one where we know the maximal temperature of the target (e.g using sensors type range-only). The density of the temperature \( T \) within the plume is a decreasing function of the horizontal distance \( \rho \) with respect to the plume center and of the elevation \( z \) above the seabed. This function is the model of the plume, which is an approximation of the actual diffusion phenomenon: the model is a probabilistic one, that expresses the probability density function (pdf) of the temperature \( T \) as a function of the distance \( \rho \) and the elevation \( z \):

\[
P(T = t|\rho, z)
\]

(1)

Figure 2 shows the behavior of the model for two different elevations: the dispersion of the temperature is also an increasing function of the distance and the elevation. Note that multiple sources do not interfere if they intersect, the water temperature being a function of the closest source (this assumption would not hold in the case of the emission of

\(^1\)Conductivity, Temperature, and Depth: is a tool for determining physical properties of sea water. It gives to scientists a the distribution and variation of water temperature, salinity, and density

\(^2\)See references cited in [8] for detailed models of this kind of phenomena.
chemicals, whose concentration augments within the intersection of plumes: such cases call for a different modeling of the pdf).

![Fig. 2: Evolution of the temperature as a function of the horizontal distance $\rho$ for the two depths $z_1$ and $z_2$ defined in figure 1. Dashed line represent the dispersion of the temperature.](image)

We chose the following equations to specify this model:

$$T_{\text{mean}} = \begin{cases} T_{\text{max}}(z) - \rho \frac{T_{\text{max}}(z) - T_0}{\rho_{\text{max}}(z)} & \text{if } \rho \leq \rho_{\text{max}}(z) \\ T_0 & \text{if } \rho > \rho_{\text{max}}(z) \end{cases}$$

where

$$\rho_{\text{max}}(z) = \alpha z$$

$T_{\text{max}}(z) = \begin{cases} T_{\text{MAX}} - z \frac{T_{\text{MAX}} - T_{\text{MIN}}}{z_{\text{MAX}}} & \text{if } z \leq z_{\text{MAX}} \\ T_0 & \text{if } z > z_{\text{MAX}} \end{cases}$

These equations model the plume as a cone, the parameters $Z_{\text{MAX}}$ and $\alpha$ respectively defining its height and aperture. This is certainly a simplification of the actual diffusion phenomenon, but any other realistic models could be handled easily.

Finally, for a given position $(\rho, z)$ in the plume, the probabilistic variations of the temperature is modeled by a Gaussian: $T = \mathcal{N}(T_{\text{mean}}, \sigma(\rho, z))$, where $\sigma(\rho, z)$ is an increasing function of $\rho$ and $z$.

(2) In the second case, the $Z_{\text{MAX}}$ is not known (we are using a bearing-only sensor), where the probability is related to a given direction of the target. The own difference between the precedent and the actual case of study is that the sensor gives the direction of the target rather than the distance. The figure 3 shows, the defined model for a given direction.

The model function is expressed by the probability density function (pdf) of the temperature $T$ as a function of a direction (deg) and the elevation $z$:

$$P(T = t|\text{deg}, z)$$

This model is specified by a simple Gaussian where $T = (T_{\text{mean}}, \sigma(\text{deg}, z))$. As a summary, an example in the figure 4 shows the two types of used sensors and the obtained map for each kind of sensor.

In particular, it makes the assumption that there are no current: a stationary current independent of the depth would simply generate an oblique cone, and the consideration of dynamic currents that are a function of depth would require a more complex parametrization.

![Fig. 3: Evolution of the temperature as a function of the degrees deg for the two depths $z_1$ and $z_2$ defined in figure 1.](image)

### III. Construction of Probability Grid

In this section, we address the problem of underwater exploration. We detail the representation of the environment and how the vehicle can reason to update and make decisions according to its constructed map.

1) **Representation of the environment.** To reduce the amount of collected data, we have represented the environment as a map that discretizes the environment into a collection of ordered cells in a regular pattern $N \times M$. Each cell $\{x_{i,j}, i \in [0,N], j \in [0,M]\}$ in the grid has a probability value ($P_k(x_{i,j})$ at time $k$), that represents the proximity of the vehicle to the target. To avoid the redundancy of exploring the same cell, another boolean value is added into the cell. This value is equal to one when at least one vehicle has reached this cell; otherwise that value is set to zero.

2) **Updating the grid.** At each new measure the vehicle has to update its grid. The update is computed incrementally according to a classical bayesian paradigm under markovian assumption:

$$P^k(x_{i,j}) = \frac{P(T^k|x_{i,j} = \text{vent})P^{k-1}(x_{i,j})}{P(T^k)}$$

The probability $P(T^k|x_{i,j} = \text{vent})$ represents the associated temperature probability if $x_{i,j}$ is the target. The probability $P^{k-1}$ represents the probability value of the target existence at the time $k-1$. The probability $P^k(x_{i,j})$ at the cell $x_{i,j}$ is the probability value implicitly representing the precision of the source location (a probability equal to 1 meaning that the source is perfectly localized).

3) **Making decisions (the strategies of exploration).** This allows to define adaptive strategies, in which the AUVs select the next motions in order to confirm the presence of a target. Given a source presence hypothesis (a local maximum of $P(x_{i,j})$ in the mapped vicinity of the current AUV position), two types of motions are defined depending on the sensor model.

(a) the motion that maximizes the source detection is straightforwardly the one that drives the AUV towards...
Fig. 4: Illustration of two strategies of exploration for target localization. The target is represented at the left of the figure. (1) represents the exploration strategy of following the maximum probability. (2) represents another exploration strategy that do not follow the maximum probability.

the direction of this maximum. A threshold can be defined to consider the source as “treated”. A value $P_{conf}$ leads to the confirmation of a source presence, but not precisely localized. The algorithm 1 explains for each measured data of one vehicle, what is the next chosen cell $x'_{i,j}$. To choose the next cell the vehicle follows the maximal value of the target. This is why in the algorithm 1 line 12 the next cell is chosen as follows:

$$\text{Max}_{a_i \in \{\text{left}, \text{right}, \text{behind}, \text{front} \}} P(x_{i,i} / x_{i,j} = \text{NotExplored})$$

(6)

**Algorithm 1** Algorithm of the next cell to explore.

**Require:** $D$: the diameter of the target; $\text{Target}_{x,y}$: the coordinate of the target; $P(x_{i,j})$: the probability that $x_{i,j}$ is the target; $a$: an action; $\tau$: a function of transition. From an action and a cell it can generate the next cell.

1: Update grid using equation (5).
2: if $(\exists i, j : i \in [0, N], j \in [0, M], P(x_{i,j}) \geq P_{conf})$ then
3: $\langle \text{Target Found} \rangle$
4: for $(\forall i, j : i \in [0, N], j \in [0, M])$ do
5: if $(0 < |x_{i,j} - \text{Target}_{x,y}| < D)$ then
6: $P(x_{i,j}) \leftarrow 0$;
7: $P(\text{Target}_{x,y}) \leftarrow 1$;
8: end if
9: end for
10: end if
11: $\langle \text{Choose Next Cell} \rangle$
12: $a \leftarrow$ using the equation (6) or (7).
13: $x'_{i,j} \leftarrow \tau(a, x_{i,j})$
14: return $x'_{i,j}$

(b) Using the bearing-only sensor defines another exploration strategy, where to localize a target is not to drive the AUV towards the direction of the maximum but it is to go into another direction that can collect more information for the exact target location.

In the algorithm 1 line 12, the vehicle uses this function to choose the next cell to explore:

$$\text{Max}_{a_i \in \{\text{left}, \text{right}, \text{behind}, \text{front} \}} f(z_{\tau(x_i,a_i)})$$

(7)

where, $f(z_{\tau(x_i,a_i)})$ is a function that predict the future values in the Map, if the chosen action is $a_i$. For example, we suppose that the target is on the left side of the vehicle. If the $a_i = \text{left}$ that implies that the next values of the cells have the same values as precedent. but, if the $a_i = \text{front}$ the probability for next cells differs. Based on this reasoning the vehicle chooses its next explored cells.

4) Adaptive Cooperative Exploration Strategy (ACES). In the case where the vehicles exchange data, the function of exploration (see algorithm 1 the line 12) depends on three criterion.

a) Predefined way-points. These points represent a passage point that the vehicle has to achieve (with priority equal to 1).

b) Opportunistic goals. These points are generated according the vehicle measure. The point is chosen according to the maximal value of the probability in the grid (with priority equal to 2).

c) Predefined communication points. These points are important for the vehicle positioning and also for data exchange. That is why, if the vehicle, because of the time delay, has to choose between the way-point, the opportunistic goal and the communication point, it will choose to satisfy the last one (with priority equal to 3).

In our approach, a priority is given for all these points. The higher the priority is the more the point is taking into account. If the vehicle, cannot achieve all the three different points at a specific time, it has to achieve at least a maximal number of them with a higher priority.

IV. COOPERATION COMPLEXITY

The effectiveness of the exploration strategy depends on the way to treat the sensed data and the way to send them. E.g.
send the strict sufficient minimal data to other vehicles to give the vehicle more time for exploration. In this section we are going to, first, give the maximal time of communication using a bandwidth of 100 bps, and second, give the complexity of the used cooperative algorithm at each vehicle to update its grid.

**Communication bandwidth and the amount of exchanged data:** we want to know what is the communication time between two vehicles. \( n_d \) represents the number of the vehicle moves and \( L \) the bandwidth (100 bps). The communication time \((com_t)\) is equal to:

\[
com_t = \frac{n_d \times |d_0|}{L}.
\]

\( |d_0| = |d_1| = \ldots = |d_i| = |x_0| + |z|x_0 \)
\( = 2 \times 16\text{bits} + 8\text{bits} = 40\text{bits} \). \( x_0 \) is the coordinates of the vehicle and \( z|x_0 \) is the amount of collected data (temperature/probability and a boolean value of the visited/not visited cells). The communication time can be represented as \( com_t = 0.4 \times n_d \). If the communication time is bounded by 2 minutes, that means that the vehicle can explore less than 15 km (each cell represents 100m). In general, because of the localization error of the vehicle, the vehicle can explore at maximum a distance of 1.2 km with a speed of 1.5m/s. This limit indicates that the vehicle will communicate less than 2 minutes, which is a reasonable communication time.

**Complexity of the cooperative update:** At each communication point, the AUV sends its new observed probability grid and receives the observed probability grid from the other AUVs by means of the ASV. To avoid data redundancy, the vehicle sends its observed grid from the latest communication point to this new communication point. The ASV keeps the latest map of each vehicle. To update the ASV map the algorithm 2 is used. The number of operation depends on the number of explored cells \( n_d \) where the number of operation is \( n_d \times N \times M \). This implies that the complexity of the MapUpdate is \( O(N \times M) \).

**Algorithm 2** Algorithm to Update the Map of the ASV.

1. for (each new explored point \((n_d)\))
2.    for \((i = 0 \text{ to } N)\)
3.      for \((j = 0 \text{ to } M)\)
4.        MapUpdate
5.      end for
6.  end for
7. end for
8. return \( Map \)

**V. SIMULATION AND ANALYZE THE RESULTS**

We implemented our results into an architecture for planning and control execution. This architecture, called T-REX, has been extensively used on one AUV at MBARI. In precedent work we have extended this architecture into a cooperative architecture [13], which is used in the following experiments.

We conducted some experiments to compare different strategies in the single and multiple AUVs case. Two types of experiments are shown, the first one are given using range-only sensors and the other experiments used range-only sensors.

**A. Range-only experiments**

The vehicle has a sensor range \( r \) and an implicit transect width \( W \) (see Fig. 7a). The strategies are compared for given values of \( r \) and \( W \) with respect to the execution time, the precision of the target location and the number of confirmed targets.

![Fig. 5: Illustration of the two strategies. Fig.(a) represents all the present targets, waypoints (X) and communication points (dots). The dark/light squares represent the starting and ending point of the mission. The dark line in the Fig.(b), represents the swathing pattern of the vehicle, without adaptation, and the probabilistic grid at the end of the mission. The light pattern at Fig.(c), represents the swathing pattern of the vehicle. With no adaptive strategy, two targets where localized out of 11. But with adaptive strategy, six of them where localized.](image)

The Fig. 5 evaluates one example of one vehicle using two types of strategy. The dark circles upper dark/white lines, represent the communication points with the ASV. The dark line represents the adaptive G.I.G (Sw.P.G.I.G) strategy and the white one represents the no adaptive (Sw.P.NoAdp). In this experiment, using the no adaptive strategy the number of localized targets is 2 out of 11 (18%). However, the G.I.G strategy localize 6 (54%): unsurprisingly, G.I.G detects more targets.

In another experiment, we setup two vehicles to explore the same area and sharing their maps to cooperate. The AUVs share data with the ASV using communication points.

We have performed the experiments with different setup and initial targets distribution. The overall mission execution time for each, mono robot and multi robots, in our experiments, is naturally reduced by the factor of two when using two AUVs. In the Fig. 6, the precedent strategies are evaluated by the number of found targets and a precision of 80%. In the criterion of found targets, the best strategy is the G.I.G by using multiple vehicles (81%).

In general, for mission execution, each criterion (the number of found targets, the precision and the exploration time) is weighted, to favor one strategy or another. In the case where
all the criterion have the same weight, the best strategy is the Adaptive G.I.G for multiple vehicles.

The coverage rate \( (r/W) \), has an impacts on the obtained results. The Fig. 7b represents two coverage percentage. The white bars represent the found targets using a 100% coverage and the black bars represent a 125% coverage. The figure shows that the more effective strategy is the G.I.G for a coverage of 125%. This percentage means that there is redundant information at the vehicle sensor. This redundancy is useful, to localize a maximal number of targets. This experiment shows us that \( r \) and \( W \) has to be set at the right values to maximize the percentage of the localized targets. Where, for each strategy, we have to find the best coverage percentage to avoid unused redundancy.

\[ r \]
\[ W \]

B. Bearing-only sensors

To show that the proposed architecture is versatile we deployed another kind of sensor, bearing-only, to localize one target using two AUVs. This target is shown in 3D in the figure 1, where each vehicle exchange its data at communication points to predict the location of the target. In the figure 8 shows the obtained exploration grid of the two AUVs and the dimension of the target at two different depths. The figure 8,(a) represents the model for the target at a depth equal to \( z_1 \) for AUV1 and the collected data by using the bearing-only sensor. The figure 8,(b) represents the target at \( z_2 \) depth and the associated perceived grid for the AUV2.

VI. Conclusion

Our contribution aims at defining an architecture and a framework to evaluate various source seeking strategies for multiple autonomous underwater vehicles. In our experiment, an autonomous surface vehicle is used to collect and redistribute sensor maps, to help the AUVs to relocalize without surfacing, and to act as a communication relay with an operator. Each AUV produces a probabilistic sensor map of possible interesting sources using different types of sensors (range-only or bearing-only), and share them with the other vehicles to improve its perception of the environment, and find the sources of interest. We propose a mechanism to allow the vehicles to share these maps. We used for our experiments an extension to the T-ReX architecture, which has already been used at MBARI to control one vehicle. This extension adds two new components (reactors), one for communication with the other vehicles and one to establish new opportunistic goals with respect to the chosen strategy. The strategy of exploration is presented where each vehicle has to weight the advantage of accurately localizing sources while respecting time constrained navigation waypoints and communication rendez-vous.

At this point we have shown that the framework is ready and can be now effectively used to evaluate more complex strategies involving the ASV (e.g. with vehicles at different depths, different transect widths, etc). Moreover, the use of an already deployed architecture is very encouraging to consider
deploying the proposed approach and the selected strategies on real systems.

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