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Synergistic AUV Navigation through Deployed Surface Buoys

Tauhidul Alam¹ , Logan Gandy¹, Leonardo Bobadilla² , and Ryan N. Smith² 

Abstract—In this paper, we present a navigation method for an Autonomous Underwater Vehicle (AUV) in an underwater environment making use of a deployed set of static water surface platforms called *buoys* on the environment. Our method has the following steps: 1) Communication regions of buoys are computed from their communication capabilities; 2) A set of feasible paths through buoys between given initial and goal locations is calculated using the preimages of the buoys' communication regions; 3) An AUV navigation path that utilizes the least number of buoys for state estimation is chosen from the calculated feasible paths. Through extensive simulations, we validated our method which demonstrates its applicability.

I. INTRODUCTION

Marine robotic systems revolutionize oceanic sampling through the collection of critical information in order to learn models for physical, chemical, and biological spatiotemporal dynamical features. Several crucial applications, such as water quality monitoring [1], coral reef exploration [2], and maritime security [3] rely on the ability to deploy AUVs effectively. However, a central challenge to the effective deployment of AUVs is the *position estimation problem* for their navigation. This is a well-known problem since exteroceptive sensors such as GPS and magnetometers do not work properly in underwater environments. Furthermore, traditional sensor modalities used for robot navigation, e.g., cameras and depth sensors, can be affected due to changes in illumination and the dynamic nature of an ocean with moving obstacles and objects.

A traditional solution to this problem for AUVs is to periodically go up to the water surface to collect GPS measurements and use dead-reckoning with IMU sensor data to obtain their position information for navigation. However, this approach has two disadvantages. First, periodical resurfacing wastes valuable energy resources. Since the battery lifespan is a constraint for an AUV, the available time should be spent collecting its desired information. Second, resurfacing can be dangerous since it may lead to collisions with commercial surface vessels, and sometimes it is undesirable during AUV covert missions.

In this paper, we propose a navigation method for an AUV in an underwater environment taking advantage of a

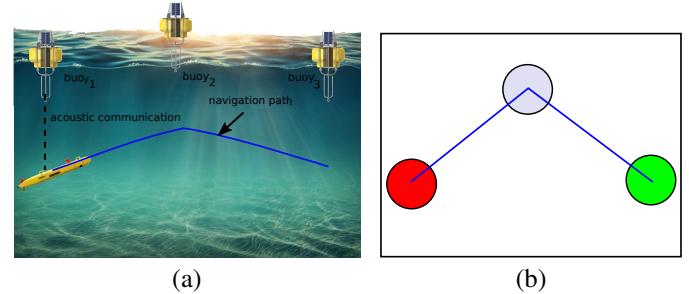


Fig. 1. (a) An AUV following a set of deployed surface buoys to obtain its state estimation for navigation in an underwater environment. (b) An example AUV navigation path (blue) along explored buoy's grey communication region on an approximate 2D representation of the environment for its initial (red) and goal (green) locations within the buoy communication regions.

deployed infrastructure of a set of *buoys* on the surface of that environment. A dynamic placement strategy of a set of surface nodes is proposed to optimize the localization performances of multiple target AUVs in underwater environments [4]. This localization approach suffers from synchronization problems, and in this setup, it is not addressed how an AUV can navigate during uncertainty in its states (positions). Another challenge for our setup is the communication between the AUV and surface buoys. Additionally, we assume that deployed surface buoys equipped with GPS and acoustic sensors can serve as a set of landmarks in an underwater environment. These buoys can communicate with an AUV using acoustic sensors and provide buoys' state information to reduce its state uncertainty for navigation, as illustrated in Fig. 1.

The motivations for using acoustic sensors for the communication between an AUV and a buoy are two-fold. First, acoustic signals attenuate less in underwater environments. Second, they are able to travel further distances. On the other hand, radio signals attenuate rapidly and optical signals scatter in aquatic environments. Therefore, we utilize deployed surface buoys' state information to reduce an AUV's state uncertainty for its navigation. Given an initial and a goal location in an underwater environment, our proposed method finds a path for AUV navigation using estimated states from a given set of deployed surface buoys.

Contributions: First, we compute surface buoys' communication regions on the basis of their communication capabilities. Second, a set of feasible paths through buoys between an initial and a goal location is calculated using preimages of explored buoys' communication regions. Third, we determine the AUV navigation path that utilizes the least number of buoys while

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estimating its positions through buoys along the path. Finally, we evaluate the variability of the AUV's navigation path for the static and dynamic deployments of buoys with different communication capabilities.

II. RELATED WORK

Aside from buoys, several other vehicles have been previously utilized for AUV localization while it is navigating through underwater environments such as manned surface vehicles, surface ships, autonomous surface crafts. The near-shore communication of a network of surface buoys with radio modems is presented [5]. An experimental cooperative localization method for multiple AUVs is proposed in [6] utilizing autonomous surface crafts equipped with undersea acoustic modems and GPS. In a closely related work [4], the authors propose an adaptive placement strategy of a set of dynamic and static surface nodes to optimize the localization performances of multiple target AUVs in underwater environments. These underwater localization approaches suffer from synchronization problems. A network of buoys is used in [7] to support underwater acoustic positioning systems and navigation techniques for AUVs.

An autonomous buoy is developed for dynamic positioning and tracking a target AUV by relaying messages between the AUV and its remote monitoring buoy on the water surface [8]. In another related work [9], the authors study the underwater sensor network localization problem which determines a position for each node in a network. They approximated a 3-D environment into its 2-D counterpart. However, they provide positions of some nodes to obtain positions of all nodes in the network making use of the knowledge of inter-node distances or ranges. An overview of underwater acoustic positioning systems based on buoys equipped with GPS receivers is presented in [10], where the position of an underwater target (e.g., AUVs, Remotely Operated Vehicles, divers) is estimated by the time of arrival of acoustic signals at a set of surface buoys. Nonetheless, the authors did not consider the effect of an underwater target's path in estimating their positions.

III. PRELIMINARIES

In this section, we define the workspace for an AUV and a set of buoys and formulate our problem of interest.

We consider a set of n buoys \mathcal{B} deployed on the surface of a region of interest in an ocean $\mathcal{W} \subset \mathbb{R}^2$, as illustrated Fig. 1(a). An AUV moves in a parallel plane \mathcal{W}' that is at a distance l down from the water surface. The distance l models the allowed acoustic communication distance between the buoys and the AUV. The AUV moves in \mathcal{W}' since it tries not to go to the surface to save energy or due to the stealth requirements of its mission. The AUV is modeled as a point robot with orientation S^1 , and its state space is $\mathcal{W}' \times S^1$, where $S^1 = [0, 2\pi]$. It is assumed that the AUV has motion uncertainty due to position errors in an underwater environment. Each of the buoys $B_i \in \mathcal{B}$, where $i \in \{1, \dots, n\}$, covers a circular communication region, $C_i \subset \mathcal{W}'$, with a radius r_i which represents a communication range, where the AUV is in contact with a buoy B_i through acoustic sensors. When the

AUV is inside a buoy's circular communication region C_i , it can use the B_i 's GPS coordinate to navigate without position errors since it has a communication contact with B_i through acoustic sensors. We call this the *perfect navigation mode* [11]. Let x be a state of an AUV that represents a geographic coordinate. The geographic coordinate of each buoy represents the coordinate of a circular communication region's center. The range r_i can vary since the communication equipment of each buoy can be different or may have disparate powers. When an AUV is outside a C_i , the AUV follows a path within a sub-region of \mathcal{W}' which we call a *preimage* for a direction d , where $d \in S^1$. Let $P(B_i, d)$ denote a preimage of a buoy B_i for a direction d . We call this the *imperfect navigation mode* [11]. A preimage $P(B_i, d)$ is a sub-region or a cone-shaped region that is bounded by two tangents and a circular edge. A set of preimages for a state x for some directions is denoted as $\mathcal{P}(x)$. Let x_I be the initial deployment state of an AUV inside or outside a C_i and x_G be its goal state within a C_i , i.e., one or more buoys can be reached from its goal state. When the AUV is deployed outside a C_i , we assume that it relies initially on its proprioceptive IMU sensors for state estimation and that it moves randomly until it reaches to a C_i . We define a path of an AUV be $\tau : [0, 1] \rightarrow \mathcal{W}'$ such that $\tau(0) = x_I$ and $\tau(1) = x_G$. In this context, we are interested in solving the following problem.

Problem 1. AUV Navigation: *Given a set of n deployed surface buoys \mathcal{B} , a set of buoys' communication regions $\mathcal{C} = \{C_1, C_2, \dots, C_n\}$, an initial state x_I and a goal state x_G in an underwater environment \mathcal{W}' , find a path τ that takes an AUV from x_I to x_G and provides estimated states from deployed buoys for navigation.*

IV. METHOD

In this section, we detail the method for solving the problem formulated in Section III.

First, we compute a set of communication regions \mathcal{C} for all deployed buoys \mathcal{B} utilizing their communication ranges. Then, we find a navigation path τ for an AUV from Algorithm 1. To achieve this, Algorithm 1 takes as input the environment \mathcal{W} , positions of deployed buoys \mathcal{B} , a set of communication regions of deployed buoys \mathcal{C} , an initial state x_I , and a goal state x_G . We consider that an AUV can move in eight different directions (N, NE, E, SE, S, SW, W, NW) outside the circular communication region C_i of a buoy B_i , where $i \in \{1, \dots, n\}$. These movements lead an AUV to a C_i to gather its state information. If an AUV navigates through the overlapping region of two or more preimages, it can choose one of them randomly. Thus, Algorithm 1 calculates a set of preimages $\mathcal{P}(B_i)$ in eight different directions for each buoy B_i that can be reached from x_G and serve as a landmark for the AUV. The lengths of these preimages depend on the radius r_i of a C_i . The larger the radius r_i , the farther out the preimages can go, and vice versa.

Afterward, it applies a process called *preimage backtracking* [11] from a C_i that can reach x_G for the first time. This process attempts to find an intermediate buoy's communication region C_l that is within a preimage in one of the eight

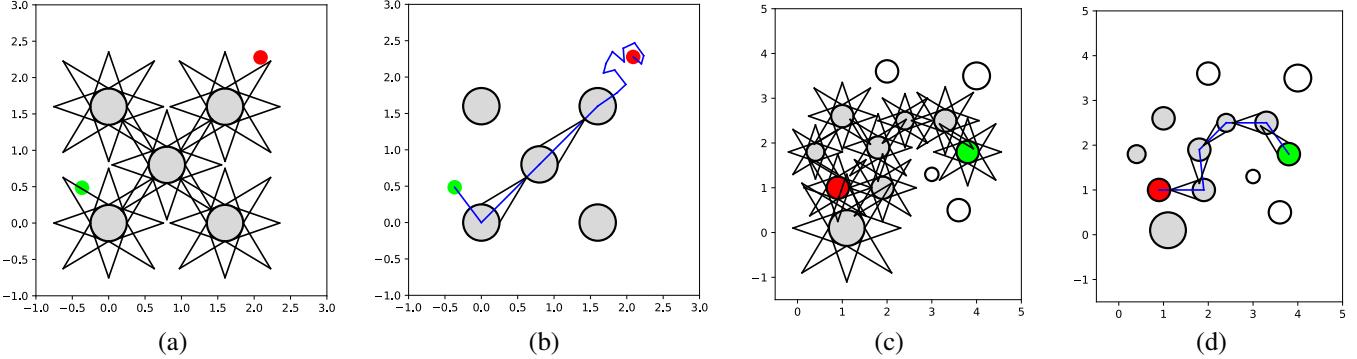


Fig. 2. Simulation results on the static placement of buoys for different pairs of initial and goal locations of an AUV: (a) Calculated preimages for eight directions for a set of buoys with circular communication regions (grey circles) and a set of initial (red circle) and goal (green circle) locations outside buoys' communication regions; (b) One navigation path (depicted with blue lines) using calculated preimages and initial random movements; (c) Calculated preimages for eight directions for a set of explored buoys' grey circular communication regions and a set of initial and goal locations inside red and green communication regions of buoys; (d) Another navigation path (depicted with blue lines) using calculated preimages.

Algorithm 1: AUVNAVIGATION ($\mathcal{W}, \mathcal{B}, \mathcal{C}, x_I, x_G$)

Input: $\mathcal{W}, \mathcal{B}, \mathcal{C}, x_I, x_G$ – Environment, buoys' positions, buoys' communication regions, initial state, goal state

Output: τ – A navigation path

```

1  $T \leftarrow \emptyset$ 
2 for each  $C_i$  that can reach  $x_G$  do
3    $\mathcal{P}(B_i) \leftarrow \text{PREIMAGECONSTRUCTION}(C_i, x_G)$ 
4    $t_i \leftarrow \{x_G\} \cup \{B_i\}$ 
5    $T \leftarrow T \cup t_i$ 
6 for  $i \leftarrow 1$  to  $|T|$  do
7   for each  $C_l$  within a preimage but not in  $t_i$  do
8      $t_i \leftarrow t_i \cup \{B_l\}$ 
9      $T \leftarrow T \cup t_i$ 
10     $\mathcal{P}(B_l) \leftarrow \text{PREIMAGECONSTRUCTION}(C_l, t_i)$ 
11 for  $k \leftarrow 1$  to  $|T|$  do
12    $\tau \leftarrow \text{NAVIGATIONPATH}(T, x_I)$ 
13 return  $\tau$ 
```

directions and add the corresponding buoy (landmark) to a navigation path. It continues to apply this backchaining process from each of these intermediate buoys until there is no longer any other reachable intermediate buoy's communication C_l . This backchaining process results in multiple paths T that can reach x_G from x_I . However, if x_I lies outside a C_i , the AUV moves randomly to reach a C_i within any calculated path. Pruning these calculated paths from x_I based on the least number of landmarks (buoys), Algorithm 1 finally finds the desired path τ .

Algorithm Analysis: The running time of Algorithm 1 is $O(n|T|)$, where n is the number of deployed buoys and $|T|$ is the number of feasible paths. Since the PREIMAGECONSTRUCTION function calculates preimages for a buoy's communication region in eight directions, its running time is constant.

V. SIMULATION RESULTS

We implemented our Algorithm 1 in simulation to calculate the navigation path for an AUV using computed buoys' communication regions. We validated our method with a set of simulation runs. Our simulation results delineate our calculated preimages (cone-shaped regions around circles) for eight directions (see Fig. 2(a) and 2(c)) for explored buoys (grey circles) while an AUV follows the navigation paths (see Fig. 2(b) and 2(d)) between given sets of initial and goal locations in simulated environments. In all the figures, the initial location is indicated by the red circle, the goal location is indicated by the green circle, and the white circles represent unexplored buoys by the AUV. We also tested the variability of our computed navigation paths for both static and dynamic (random) placement of buoys. Fig. 3 demonstrates the change in the calculated navigation paths for static and dynamic placement of buoys with the same communication range for the same pair of initial and goal locations of the AUV. Fig. 4 shows the change in the calculated navigation paths for static and dynamic placement of buoys with varying communication ranges for the same pair of initial and goal locations of the AUV. We have also demonstrated in Fig. 2(b), Fig. 3, and Fig. 4 that the AUV moves randomly until it reaches to a buoy's communication region when it is deployed outside a communication region.

VI. SUMMARY AND FUTURE WORK

We have presented a navigation method for an AUV that uses an established infrastructure of surface buoys for navigation and for estimating the AUV's positions along its path. Our method can have applications in scenarios where resurfacing for GPS is dangerous, energy wasteful, or against the stealth requirements of the mission. There are several exciting directions for future work.

In our work, we made the assumption that the AUV can move in eight possible directions to simplify the calculation of preimages. In the short term, we will first remove this assumption allowing to move the robot in all potential directions by extending the ideas presented in [11]. After this, we

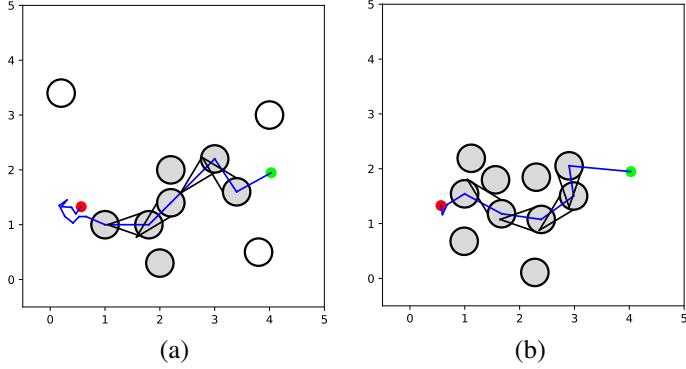


Fig. 3. Simulation results on both static and dynamic placement of buoys with the same communication range for the same pair of initial and goal locations of an AUV: (a) The navigation path (depicted with blue lines) for the static placement of buoys using calculated preimages; (b) The navigation path (depicted with blue lines) for the dynamic placement of buoys using calculated preimages.

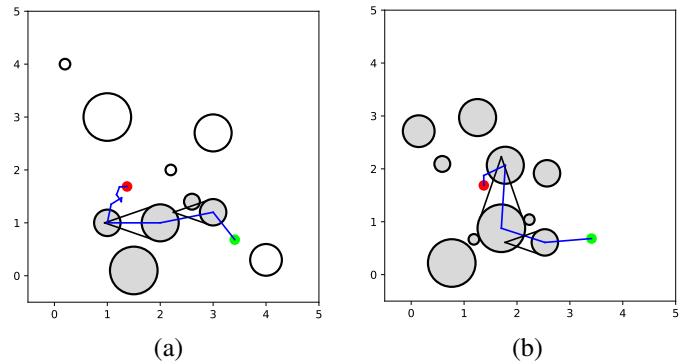


Fig. 4. Simulation results on both static and dynamic placement of buoys with varying communication ranges for the same pair of initial and goal locations of an AUV: (a) The navigation path (depicted with blue lines) for the static placement of buoys using calculated preimages; (b) The navigation path (depicted with blue lines) for the dynamic placement of buoys using calculated preimages;

will incorporate more realistic kinematic and dynamic motion models for AUVs [12] and account for ocean currents [13].

When the AUV is located outside a communication region, we assume that it relies on its proprioceptive sensors and randomness to reach another communication area. We are currently interested in devising randomized strategies coupled with state estimates that can reduce the time the AUV wanders finding a new communication region. Randomization is a powerful tool to solve robotics problems [14], [15], and the use of adaptive random walks [16] is a promising direction in this context. Our approach uses installed buoys that can provide the state information and serve as landmarks to help underwater navigation. One interesting problem is finding a placement of the landmarks to have navigation guarantees given an environment and communication radio capabilities. Results in the landmark placement for robot localization [17], [18] can serve as a starting point for this research direction.

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