Unmanned Underwater Vehicle Collaborative Missions

A Decentralized Approach to Operating UUV Teams

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***Abstract*—We describe an approach for performing unmanned underwater vehicles (UUV) collaborative missions that accounts for the limitations of operating underwater. We implemented a decentralized model predictive control (DMPC) algorithm that controls teams of UUVs while simultaneously optimizing vehicle control inputs to account for the limitations of operating in an underwater environment. We formulated challenges and limitations, such as vehicle to vehicle communications and collision avoidance, as sub-objectives that are directly included in the optimization problem rather than treating them as constraints. This allows the vehicles to dynamically prioritize the sub-objectives in situ and ensure a solution to the optimization problem. Additionally, we broke down the mission into collaborative tasks that allows for a dynamic mission in cases of unplanned circumstances, such as a lost UUV. We demonstrated this scheme in a simulation of a mine counter measure (MCM) scenario in which a heterogeneous mix of UUVs collaborated to detect, locate and report mine like objects.

I. Introduction

UUVs are noted for their ability to carry out dangerous or mundane maritime operations, such as MCM missions, harbor patrol, and oceanographic sampling [1]. The ability for teams of UUVs to cooperatively complete operations is attractive since it compresses mission time and enables operations over larger areas [2].

In collaborative missions, it's necessary to maintain communication throughout a team of vehicles to avoid the risk of limiting the team's efficiency by repeating or not completing work assignments. Keeping constant communication throughout a team of ground or air vehicles is achievable as they typically have ample bandwidth to report status information, such as position and intent, to their robotic teammates. However, this poses a problem for underwater vehicles, as they're often limited in sharing information due to the bandwidth restrictions of acoustic communications.

Acoustic modems typically broadcast data for several seconds at a time [3], creating an additional constraint on underwater acoustic communication. If multiple vehicles broadcast on a time aligned schedule, say from start of vehicle *#1's* broadcast to end of vehicle *#N*'s broadcast, it can take more than a minute. Consequently, it's necessary to employ an algorithm that plans for UUV paths past only seconds in the future. This way, other vehicles in the team can maintain awareness of its teammates' intent.

In this work, we describe an approach to address the limitations of an unmanned vehicle team operating in an underwater environment. The DMPC algorithm optimizes multiple sub-objectives that represent such limitations to create a path plan for the individual vehicle. This path plan is compressed and sent throughout the team to solve the DMPC algorithm and serve as a representation of intent in between periods of communications. Collaborative mission planning is performed dynamically, informed by each UUV's shared path plan.

In addition, the tasks of the mission are designed to limit the necessary communication between each vehicle. To address the performance constraints of acoustic modems, we introduced a communication scheme between the UUV team and a unique representation of the overall vehicle state that limits message size. Our approach is demonstrated through an MCM mission comprised of a series of collaborative tasks including search, waypoint navigation for classification, and communication bridge to a remote operator to report its findings. In the mission, the UUV team preserved the communication channel and successfully completed the mission suing channel capacity within the bandwidth limits of modern acoustic modems.

II. Related Work

There's been several studies using teams of UUVs to perform collaborative missions, such as MCM. However, past work has only focused on using centralized control schemes with pre-planned missions, where the paths of each vehicle for the entire mission is known ahead of time due to low-bandwidth acoustic communication [4]. For an underwater team, a decentralized approach is more desirable to avoid a single point of failure and problems caused by intermittent communication [5] [6]. The DMPC control scheme enables decentralized planning for the team.

Several studies apply traditional Model Predictive Control algorithms to UUVs to avoid obstacles and accurately track a reference path [7]. Our approach uses some of the traditional concepts to formulate sub-objectives to optimize communication. Prior research on incorporating UUV communication goals into UUV path plans includes the work of [8]. The algorithms developed show the ability to find optimal path plans that simultaneously balance goals of reference tracking and communications. While the focus of [8] was on

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optimizing a path plan to communicate with a stationary node, our scheme extends to the case of optimizing communications between several mobile nodes using a DMPC approach.

Existing research co-optimizes UUV motion plans for task completion and communications to a stationary node [3], but we expand that work to examine the case of several moving nodes, effectively balancing the need for communications with the desire to efficiently complete tasks in parallel.

III. Approach

A. Decentralized Model Predictive Control

The backbone of the DMPC is the formation and optimization of the objective function. The objective function is formulated as a constrained nonlinear problem in order to allow for easy integration of new sub-objectives. For this simulation, three sub-objectives were modeled to represent the necessary conditions to operate a collaborative UUV team: a waypoint objective, a communications objective, and a collision avoidance objective.

First, we formulate each sub-objective then combine them to form the overall objective function. In practice, each vehicle individually solves its own objective function.

1) Waypoint Sub-Objective

The DMPC solves the lower-level path plan. Waypoints that direct the vehicle are generated by the higher-level planning and task exaction and may change in situ to adjust to new conditions. The waypoint sub-objective (f_w) remains agnostic to this process and is simply provided with the reference waypoint at each timestep as shown in (2).

$$f_w = \|X_k^i - X_k^{i,ref}\|_2 \tag{2}$$

Where X_k^i is the state matrix of vehicle *i* at time *k* and $X_k^{i,ref}$ is the reference waypoint of vehicle *i* at time *k*.

2) Communications Sub-Objective

The communications sub-objective's goal is to keep a vehicle within a certain radius of the other vehicles. This distance is determined by the signal to noise ratio for a vehicle's acoustic modems operating in a specified environment. Every vehicle does not have to be within a certain distance of other vehicles to maintain a network of communication throughout the team. However, there must be a single, uninterrupted link between all team members to maintain communication. Fig. 1 shows the difference in output between a naïve proximity-based communications keeping approach and a network aware approach.

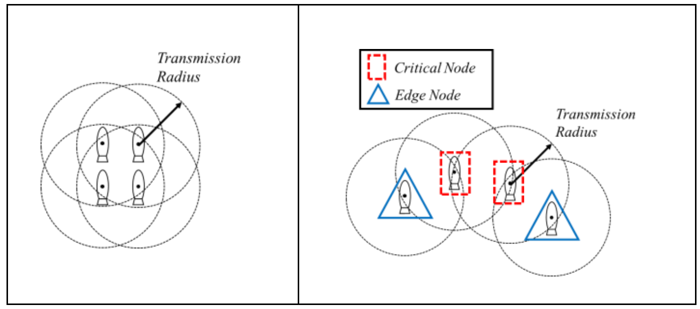

Figure 1: UUV teams are more constrained in their movement plans and overall efficiency when operating with a naïve network approach (top) compared to the network aware approach (bottom) used by our algorithm.

$$f_c = E f_{ce}(X_k^i, X_k^N) + C \sum_{j \in g(i)} f_{cc}(X_k^i, X_k^j) \tag{3}$$

$$f_{ce} = \left[\tanh\left(\|X_k^i - X_k^N\|_2 - d_{max}\right) + 1\right] * \|X_k^i - X_k^N\|_2 \tag{4}$$

$$f_{cc} = \left[\tanh\left(\|X_k^i - X_k^j\|_2 - d_{max}\right) + 1\right] * \|X_k^i - X_k^j\|_2 \tag{5}$$

Where $E \in [0,1]$ is the edge node coefficient. It is 1 for a vehicle that is an edge node and 0 otherwise. $C \in [0,1]$ is the critical node coefficient, which is 1 for a vehicle that is a critical node and 0 otherwise. X_k^N is the state of the nearest neighbor vehicle at time *k* and *g(i)* is the set of vehicles directly connected to vehicle *i*. Therefore X_k^j is the state of the j^{th} connected vehicle at time *k*. Finally, d_{max} is maximum distance allowable for communications to take place.

3) Collision Avoidance Sub-Objective

Due to the potential proximity of vehicle operations, it's necessary to optimize path plans to avoid collision. To accomplish this goal, the collision avoidance sub-objective (f_a) is formulated as shown in (6).

$$f_a = \sum_{j \in g(i)} \left[-\tanh\left(\|X_k^i - X_k^j\|_2 - d_{min}\right) + 1\right] * e^{-\left(\|X_k^i - X_k^j\|_2 - d_{min}\right)} \tag{6}$$

Where d_{min} is the minimum distance that any two vehicles can safely be from each other.

4) Optimization Problem

These sub-objectives are combined to create the overall optimization problem as shown in (7). This leaves open the ability to add in new sub-objectives as mission requirements change.

$$\begin{aligned} \min_{\boldsymbol{u_k}} & \sum_{k=1}^{N_p} f_w(X_k^i, X_k^{i,ref}) + f_c(X_k^i, X_k^N, g(i), E, C) + f_a(X_k^i, g(i)) \\ \text{s.t. } & x_k^i = f(x_{k-1}, \boldsymbol{u_k}) \\ & \boldsymbol{u_k^i} \in [\boldsymbol{U_{LB}}, \boldsymbol{U_{UB}}] \end{aligned} \tag{7}$$

Where U_{LB} and U_{UB} are the respective lower and upper bounds on the control inputs and N_p is the time horizon, in timesteps, to project into the future.

B. Collaborative Tasks and Behaviors

We implemented two distinct behaviors that made up the MCM mission: (1) collaborative search and (2) communication bridge. These behaviors are designed to create a dynamic mission, where the vehicles are only given a high-level mission and do all mission planning dynamically, while also limiting the necessary communication between each vehicle.

1) Collaborative Search

One of the goals in creating the MCM search behavior is to keep the fairly deterministic path plans used in typical MCM search routines in order to guarantee coverage of areas, improve probability of detection rates, and have more repeatable mission compared to strictly emergent behaviors. At the same time, a strictly deterministic approach would not take full advantage of a team that can dynamically reallocate resources (e.g. when team members stop to investigate possible threats or are damaged). To manage these two desires, a hybrid approach was developed that uses rule-based planning to dynamically allocate sections of the search space to each of the vehicles (Fig 2).

Pre-mission, the search area is decomposed and labeled into search lengths comprised of path segments so that each member of the team has an identical break-down of the search area. Throughout the mission, the vehicles dynamically find the next path segment to search based on costs/heuristics based on the following rules: (1) complete closest search path in your current search length; (2) complete the closest search path in a search length that isn't currently pursed by teammates; and (3) complete any outstanding (non-searched) search paths, beginning with the closest. Each vehicle finds the next optimal path segment for itself and the other team members using the DMPC path as a proxy. In each vehicle status message to the rest of the team, the vehicle includes its current segment and completed segments, all indicated by their label. This limits the communication necessary between each vehicle while still allowing the entire team to have a shared state of the environment and mission.

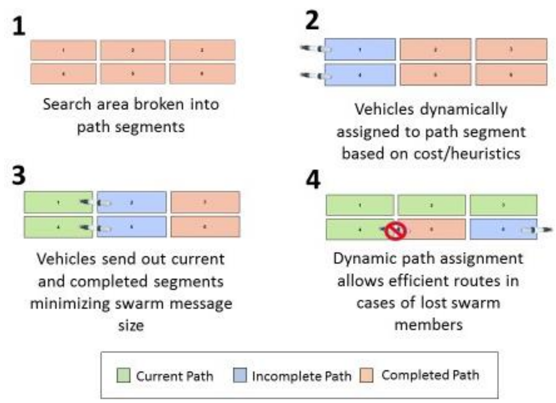

Figure 2: The dynamic search method allows the team to search a space in parallel, and includes methods to complete the search with the loss of team members.

2) Communication Bridge

The communication bridge task allows vehicles to send information from a distant operating area back to a remote operator. In order to keep the entire team together and in communication, the vehicles form daisy-chain network (Fig. 3) where information is passed from vehicle to vehicle until it's received by the operator. Aside from keeping the team in communication, this formation allows the team, as a whole, to conserve energy and the quicker vehicles of the heterogeneous team to travel further distances, cutting down on mission time.

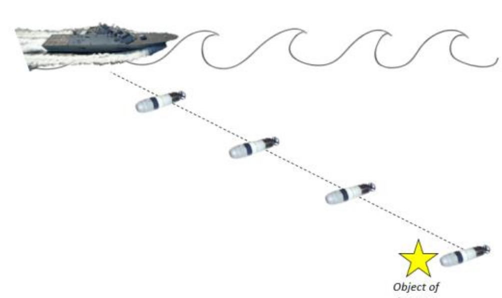

Figure 3: UUVs autonomously coordinate to create a communication bridge formation in order to relay data

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back to the host ship. In the case of an MCM mission, the object of interest would be a mine like entity.

To create the communication bridge, each of the *n* UUVs calculate *n* positions in the water such that each adjacent segment is equidistant and within communication range. Each UUV uses a Hungarian assignment algorithm to assign itself and its team members a position in the communication bridge. The algorithm generates a cost matrix based on the n communication bridge positions and each vehicle's current position estimated by the transmitted path plans. Assuming that each vehicle has approximately the same state of the team, the cost assignment algorithm ensures that two vehicles are never assigned to the same location despite the fact that each vehicle independently solves the assignment problem.

C. Vehicle to Vehicle Communications

Each vehicle has a limited communication range and takes turns transmitting by strictly following a *n* second per vehicle transmit schedule, where *n* is an adjustable period of time based on the communication requirements of the mission. During the vehicle's communication slot, the vehicle reports its own status as well as status of every vehicle it heard from in the past two communication cycles. This ensured full connectivity and awareness of the team. The time horizon, N_p, implemented in the DMPC was based on the length of these communication cycles.

To limit data sent, every reported position and path plan is encoded using a grid encoding scheme as described in Fig. 4.

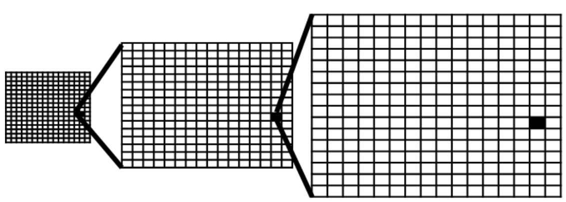

Figure 4: Grid encoding that allows any position in a 150km^2 area to be represented by 3 bytes with a 3m resolution

IV. Simulation and Results

We simulated a team of 4 heterogeneous UUVs, comprised of two types of UUVs that implanted the low-communication approach to perform a collaborative mission, specifically an MCM mission. Each UUV of the team implemented the DMPC control scheme and the simulation was executed as shown in Fig. 5.

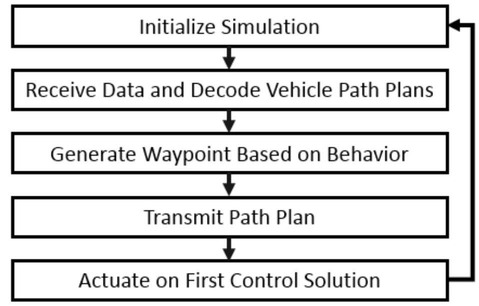

Figure 5: Simulation flowchart that details how each vehicle generates its path plan.

We created a robust simulation using an internally developed autonomy framework, Modular Extensible toolkit for Intelligent Systems (METIS) and underwater simulation environment (Fig. 6). This is one of the main autonomy frameworks used for Lockheed Martin Advanced Technology Laboratories' autonomous vehicle development. METIS has been used onboard UUVs for missions that include oil inspection, search, and most recently, multi-vehicle collaborative missions [9].

For this simulation, the DMPC, MCM behaviors, and specific mission details were implemented within the METIS framework. We created a robust asynchronous simulation environment where each UUV was independently simulated, running its own autonomy software (METIS) and vehicle control model. Each vehicle simulation was able to send messages to the members of the team via a simulated communication layer.

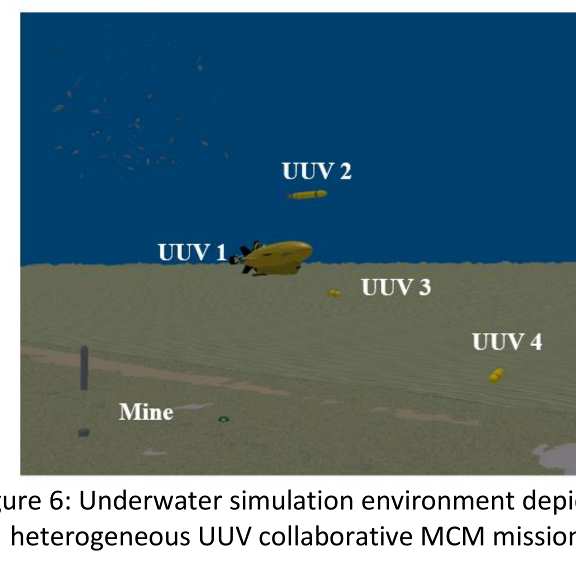

Figure 6: Underwater simulation environment depicting heterogeneous UUV collaborative MCM mission.

In the METIS-based framework, we simulated each task of the MCM mission and showed how the DMPC

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optimization affects each vehicle's trajectories. The vehicles initially were sent out to do a collaborative search of an area, shown in Fig. 7. UUV2, UUV3, and UUV4, which were all type A, performed the search and sent out messages with potential Mine-Like Entity (MLE) locations, using the grid encoding technique. UUV1, of type B, shadowed the rest of the team, waiting for potential MLE locations to further investigate. The vehicles were able to completely search the area while keeping in communication range of each other. Even though this mission was dynamically planned, the resulting search pattern was similar to a lawn mower pattern, which is typically used for a search mission.

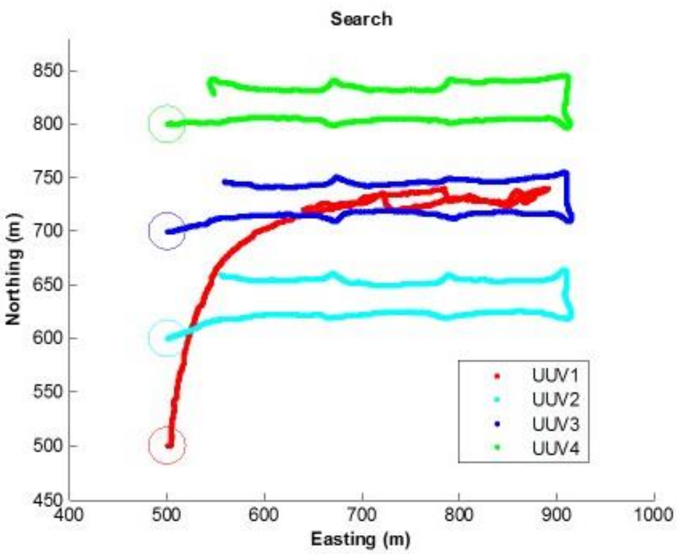

Figure 7: UUVs 2-4 perform a coordinated MCM search, while UUV 1 trails them ready to investigate potential MLEs.

After the search was completed, the team relayed information back to the host ship, so it organically forms a communication bridge (Fig. 8). The scenario shows an example of the effects of the DMPC in path planning. Fig. 11a shows that, without including the communication objective, UUV 1 took the most direct route to its intended waypoint while Fig. 11b shows that due to the communication objective, UUV 1 planned its route to stay in communication with the rest of the vehicles.

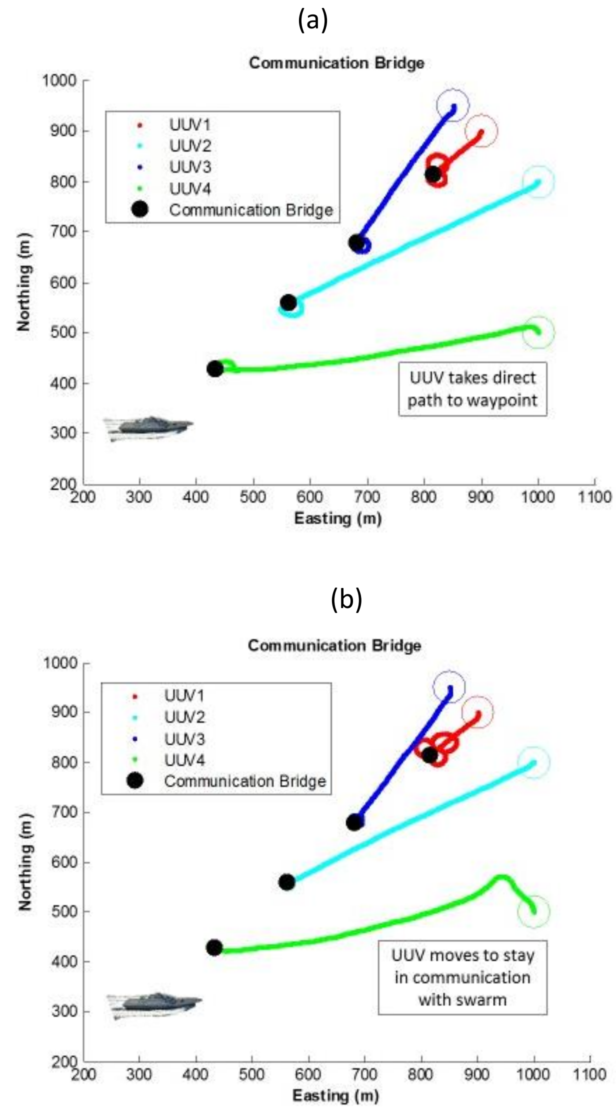

Figure 8: Simulated communication bridge. (a) Communication sub-objective **is not** included in the DMPC (b) communication **is** included in DMPC optimization.

V. Conclusions and Future Work

The simulations successfully show the implementation and effectiveness of a communications aware approach for collaborative UUV missions. The DMPC technique for multi-UUV path planning optimized vehicles' trajectory based on mission critical variables, rather than the traditional method of path planning that is constrained by these mission critical variables. This method scales well to increasing UUV teams and allows the ability to co-optimize the path plan with **multiple**

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sub-objectives (mission critical variables) instead of over-constraining the optimization problem. Additionally, typical teaming schemes are a centralized process that requires significant communication traffic between each team member to coordinate plans and keep a synchronized state of the world and mission. By switching to a decentralized planning approach, designing behaviors to require low communication, and creating a unique communication scheme between the team, we demonstrated a collaborative UUV team mission within a low communication budget.

As future work to offer a fuller approach for collaborative UUV missions increases, a more robust scheme for task allocation must also be included. Our approach only addresses dynamic re-tasking within each high-level behavior (search, communication bridge, etc.). However, its's necessary to allow for dynamic re-tasking of the high-level behaviors as well for persistent mission. In these instances, task allocation schemes that purposefully limit communication between teammates, as offered by [10], would be most appropriate.

This work is not only applicable to UUV teams, but can be applied to any UxV team operating in a low communication environment in any domain. The DMPC formulation can be used in a broad number of applications, especially since sub-objectives can be easily created and added to the DMPC optimization based on the requirements of the mission. As our approach scales well with increasing UUV teams, this lays the groundwork for implementing low-communication underwater swarms of autonomous vehicles.

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