Adaptive and Informative Planning for an Underwater Vehicle-Manipulator System

Dongsik Chang, Scott Chow, Timothy R. Player, and Geoffrey A. Hollinger

***Abstract*— Underwater motion planning is challenging due to environmental conditions such as low visibility, uncertain environmental disturbances, and complex hydrodynamics. Since these conditions pose various limitations on sensing, actuation, power, and communication, state-of-the-art solutions developed for robotic systems in the ground and aerial domains may not generalize well to the underwater domain. In this paper, we present our ongoing work to overcome these challenges and improve autonomy for underwater vehicle-manipulator systems on underwater tasks such as object retrieval. We develop a framework for planning vehicle trajectories that collect information of an object of interest in the presence of environmental disturbances. Preliminary results are shown using a closed-loop rapidly-exploring random tree algorithm. Alongside vehicle motion planning, we also present a framework for exploratory and exploitative grasp planning using underwater tactile sensing. Together, these frameworks provide a promising solution for robust underwater grasping under uncertainty.**

I. Introduction

Underwater tasks such as ship hull cleaning, pier maintenance, and environmental sampling are commonly completed with remotely operated vehicles (ROVs) or human divers. Deploying ROVs is expensive, with even small vehicles costing tens of thousands of dollars per day to deploy, in large part due to the high level of expert involvement required of the human operators, who must constantly monitor and control the robots. Using human divers is similarly expensive and carries the additional risk of hazard to life and limb caused by manned underwater operation at depth. These extreme monetary and human costs motivate a need for increased autonomy in underwater intervention and sampling tasks. By using autonomous robots to perform a greater portion of the work for underwater tasks, underwater operations can be performed safer and at lower cost than is currently possible [1].

Although autonomous robots have achieved remarkable performance at tasks in structured laboratory and industrial environments, real-world environments often pose unique challenges to robotic manipulation that cause algorithms designed for more structured environments to fail. The underwater domain is particularly challenging in part because difficult visual conditions, including turbid water and shifting lighting, cause perception algorithms that were designed for terrestrial domains to fail underwater. Additionally, underwater robots face constrained power and computational resources compared to land-based robots, and the high cost of underwater deployment has resulted in a comparative dearth of underwater robotics datasets, which limits the applicability of deep learning-based approaches that often require large datasets to train. Finally, uncertain currents and nonlinear hydrodynamics make it challenging to plan efficient and dynamically feasible paths.

The Resident Seabed Autonomy (RSA) project [2], a collaboration between the Applied Physics Laboratory at the University of Washington and the Collaborative Robotics and Intelligent System Institute at Oregon State University, aims to overcome these challenges and improve autonomy for underwater vehicle-manipulator systems (UVMS). As part of the project, we are conducting fundamental research in control, perception, planning, and human interfaces to enable dexterous, robust, and flexible robotic manipulation in underwater environments, improving the efficiency and reliability of underwater manipulation. In this paper, we provide the current status of our work in addressing problems in motion planning involving active perception with a UVMS.

Fundamental challenges in underwater manipulation arise in object retrieval tasks, in which an object is secured and removed from the seafloor. Our work targets these tasks because they are similar in a wide variety of underwater tasks. We integrate adaptive and informative motion planning into vehicle navigation and robotic arm manipulation. By analyzing the motion of the UVMS coupled with the environment, we design UVMS motions that can adapt to underwater disturbances such as ocean currents. For effective operation of the UVMS with limited information in the underwater environment, we investigate design of UVMS motion to maximize information to be collected from visual and tactile sensors. Furthermore, to increase the success rate of manipulation tasks, we conduct grasp planning using information from visual and tactile sensors.

The rest of the paper is organized as follows. Section II provides a discussion of related work in motion planning and grasping. In Section III, we provide an overview of informative kinodynamic motion planning and adaptive replanning that we plan to explore in our project. Section IV discusses the tactile exploration and grasp planning problems for gathering data and executing successful graphs, and Section V introduces software tools used to analyze the motion of our hardware systems in the underwater environment. Finally, we end in Section VI with concluding remarks about the integration of motion and grasp planning pipelines.

This work was supported in part by ONR award N0014-21-1-2052 and ONR/NAVSEA contract N00024-10-D-6318/DO#N0002420F8705 (Task 2: Fundamental Research in Autonomous Subsea Robotic Manipulation).

The authors are with the Collaborative Robotics and Intelligent Systems Institute, Oregon State University, Corvallis, OR 97331, USA (email: {changdo, chows, playert, geoff.hollinger}@oregonstate.edu).

II. Related Work

In this section, we provide a brief overview of related work in motion planning and grasping relevant to the underwater manipulation domain.

A. Motion Planning

1) Adaptive Planning with Uncertainty: Motion planning without environmental uncertainty is often approached using sampling-based methods such as Rapidly-exploring Random Trees (RRTs) [3]. Motion planning in uncertain environments applies sampling-based methods to two related problem domains. First, there is planning with uncertainty, in which the structure of environment is known beforehand, but there is either state uncertainty or uncertainty in dynamics that makes some paths riskier than others. Prior work that has addressed planning with uncertainty include Rapidly-Exploring Random Belief Trees [4], which incorporates state uncertainty into sampling-based planning by representing states as Gaussian and planning over the belief space to minimize uncertainty.

Second, there is adaptive replanning, which seeks to address the issue where the location of the obstacles and/or traversal costs is unknown or partially known during planning, and only during execution does the agent observe the actual state of the world, thus requiring replanning during execution. RRT^{X} [5] is one approach that has examined extending the traditional RRT algorithm to allow for replanning by quickly updating the tree based on new information to leverage previous samples. Risk-Aware Graph Search [6] examines the problem from a search-based planning perspective by encoding edge costs as probability distributions whose true value is uncertain until exploration and finding the lowest risk path in the graph. In our work, while we may have an estimate of the world based on prior knowledge from ocean modeling, these estimates may be inaccurate or outdated, therefore there is a level of uncertainty involved. Thus we aim to incorporate these two areas of research to adaptively replan with uncertain estimates of the world state.

2) Informative Kinodynamic Motion Planning: Despite increasing attention to UVMS motion planning, existing work has not incorporated either underwater manipulator dynamics or underwater vehicle-manipulator dynamics yet. Conventional RRT algorithms are developed for holonomic robots. For underwater vehicle motion planning with differential constraints, [7] has incorporated vehicle dynamics into a closed-loop rapidly-exploring random tree (CL-RRT) for an autonomous underwater vehicle. Given a sampled node in the configuration space, this work first computes vehicle heading and depth control commands to reach the sampled node by using fuzzy controllers and then computes a feasible node by running a vehicle dynamics model for the heading and depth control commands. However, their work does not address the problem of information gathering and their rule-based fuzzy controller may limit navigation performance.

For informative vehicle motion planning, [8] has incorporated the Fisher information into a CL-RRT without considering underwater domains. For informative manipulator motion planning, much of the related work focuses on tactile exploration in indoor lab settings. To the best of our knowledge, our work is the first to apply this line of work to the underwater domain considering vehicle-manipulator dynamics.

3) Planning for Underwater Vehicle-Manipulator Systems: In [9], the Girona 500 vehicle was used to execute a valve turning task underwater. They used the multirepresentation, multiheuristic A* algorithm to plan paths for a UVMS using motion primitives designed separately for vehicle and robotic arm. To identify the valve, they used a purely vision-based system with a series of filtering and edge detection image processing techniques to locate the orientation of the valve. Finally, visual servoing with an arm-mounted camera was used to align the manipulator with the valve and turn it.

In our work, we consider a turbulent environment with a lower weight class vehicle, which will cause the UVMS to deviate from plans generated without considering system dynamics and environmental uncertainty. We plan to use a more sophisticated perception system integrating tactile sensors and laser scans to perform grasps on a variety objects.

B. Grasping

Advances in robotic grasping in structured environments have been achieved with the advent of data-driven algorithms to identify secure, feasible grasps and the increasing availability of large grasping datasets [10]. Given a model of the target object, these grasp synthesis algorithms output end-effector configurations likely to seize the object without slipping during manipulation. While early algorithms to identify secure grasps focused on optimizing geometric properties of the grasp such as force closure [11], more recent work has formulated the problem of maximizing grasp success as a learning task in which vast quantities of data inform a grasp selection policy that maximizes empirical or simulated success rates [12]–[14].

Collecting underwater grasping datasets is expensive and slow, and to our knowledge no such large datasets have been collected. Consequently, state-of-the-art autonomous underwater manipulation systems rely on simple analytical rather than data-driven measures of grasp quality. For example, the Girona 500 vehicle executed grasps after just performing simple alignment of a gripper to a valve [9]. Similarly, the University of Hawaii's semi-autonomous underwater vehicle for intervention missions (SAUVIM), an early UVMS, used only visual localization and servoing controls to verify geometric alignment of the end-effector and target to in underwater manipulation tasks [1]. Existing implementations such as these use simple geometric heuristics to enable underwater manipulation. Adapting terrestrial grasp synthesis techniques to the underwater domain is a key effort of this project to enable higher levels of UVMS autonomy.

III. Adaptive and Informative Underwater Motion Planning

We consider a UVMS navigating from the initial position at $\mathbf{r}_{\text{start}}$ to an object of interest locating at $\mathbf{r}_{\text{goal}}$ and exploring the object using a robotic arm for manipulation tasks under uncertain environmental disturbances D. Let $\mathbf{r}^v$ and $\mathbf{r}^a$ denote the state of the vehicle and manipulator, respectively. Also, let $\mathbf{u}_k$ and $\mathbf{r}_k = [\mathbf{r}_k^v, \mathbf{r}_k^a]$ denote the control input and state of the UVMS at time step k, respectively. Action $\mathbf{u}_k$ includes vehicle thruster and robotic arm joint inputs that influence how the UVMS is actuated. These actions can cause information to be accumulated about the target object according to observations from sensors.

A key to increasing the success rate of manipulation tasks by the UVMS is to maximize information about the target object, such as its pose and shape, gathered during navigation and exploration prior to manipulation tasks. This kinodynamic motion planning problem can be formulated as the following optimization problem:

$$U^\star = \operatorname*{argmax}_{U \in \mathcal{U}} I(U|D), \tag{1}$$

$$\text{subject to } \mathbf{r}_{k+1} = f(\mathbf{r}_k, \mathbf{u}_k), \tag{2}$$

$$\mathbf{r}_0^v = \mathbf{r}_{\text{start}},\ \mathbf{r}_f^a = \mathbf{r}_{\text{goal}} \tag{3}$$

where $U = \{\mathbf{u}_0, \cdots, \mathbf{u}_k\} \in \mathcal{U}$ is a sequence of actions, f represents underwater vehicle-manipulator dynamics, and $I(U|D)$ is a function representing the information quality gathered by performing the action sequence U given the environmental disturbances D. In this problem, we consider any quantifiable metric for information of interest, such as Fisher information or entropy, along the trajectory.

Since the UVMS motion is subject to environmental disturbances such as ocean currents in dynamic environments [15], it is critical to incorporate these disturbances in (1). For example, the quality of information obtained by the sensors of the vehicle may be significantly degraded when the vehicle is moving against the current. Additionally, moving against the current is more costly in terms of energy expenditure, which is an important consideration in underwater domains.

However, it is possible for the actual currents experienced by the vehicle during plan execution to differ from the estimated currents used during planning, especially if the underlying model for the ocean currents is inaccurate or the ocean conditions have changed significantly. Thus, we plan to address the uncertain disturbance planning problem, where an estimate of ocean current disturbances based on prior knowledge is maintained. This estimate is used in the initial planning phase. As the robot executes the plan and collects information on the actual state of the world this estimate is updated and used to actively replan.

A. *Reduced Dimensionality Problem Formulation*

To facilitate algorithm development to solve (1), initial progress has been made on vehicle motion planning in a simplified two-dimensional (2D) problem domain as a proof of concept. While the actual problem is formulated in a three-dimensional (3D) environment with 12 degrees-of-freedom vehicle dynamics and an unknown spatiotemporally-varying current field, we are limiting our preliminary analysis to a 2D environment without environmental disturbances. However, to expedite extension of our results obtained through this study to 3D later, we do not limit vehicle dynamics. First, we investigate incorporating vehicle dynamics under no environmental disturbances into CL-RRT. To be specific, in expanding a tree in CL-RRT, we investigate using model predictive control (MPC) with vehicle dynamics as constraints to connect a new sampled node to an existing one. Let us denote an existing node by q_{start} and a sampled node by q_{target}. To generate a dynamically feasible trajectory for a UVMS, we generate a series of vehicle control inputs by solving the following optimization problem formulated as in an MPC framework:

$$\mathbf{u}^\star_{0:N-1} = \operatorname*{argmin}_{\mathbf{u}_{0:N-1}} \sum_{k=1}^{N} \|\mathbf{r}_k^v - q_{\text{target}}\|^2 \tag{4}$$

$$\text{subject to } \mathbf{r}_{k+1} = f(\mathbf{r}_k, \mathbf{u}_k),\ \mathbf{r}_0^v = q_{\text{start}}, \tag{5}$$

where N is the prediction horizon. Then, to track the planned trajectory between the two nodes, a UVMS executes the control inputs.

Additionally, we aim to incorporate information gathering into CL-RRT, referred to as informative CL-RRT, and investigate the case on the horizontal plane for simplicity. Suppose a UVMS obtains the distance and angle information of an object relative to the UVMS from its perception system while navigating towards the object. To plan UVMS motion that maximizes the information, we can employ the Fisher information which implies the amount of information about the estimation variable contained in the observation. Let us denote the position of a target object by $\mathbf{s} = [s_x, s_y]^T$ and the horizontal position of a UVMS by $\bar{\mathbf{r}}^v = [r_x^v, r_y^v]^T$. The observation vector, denoted by $\mathbf{z}$, for the distance and angle information of an object relative to the UVMS can be constructed as $\mathbf{z} = [\text{dist}(\mathbf{s}, \bar{\mathbf{r}}^v), \text{angle}(\mathbf{s}, \bar{\mathbf{r}}^v)]^T$. Assuming observation noise is represented by zero-mean Gaussian with covariance σ^2, the Fisher information matrix regarding $\mathbf{s}$ contained in $\mathbf{z}$ can be computed by

$$I_{\mathbf{s}}(\mathbf{z}) = \frac{1}{\sigma^2}\Big(\frac{\partial \mathbf{z}}{\partial \mathbf{s}}\Big)^T \Big(\frac{\partial \mathbf{z}}{\partial \mathbf{s}}\Big). \tag{6}$$

Compared to [8], our work specifically aims to investigate dynamic feasibility of planned trajectories for a UVMS in the underwater domain by incorporating the MPC framework shown in (4) into informative CL-RRT.

Initial results, shown in Fig. 1, have indicated the potential applicability of these techniques to the underwater domain. The figure contains the output of our preliminary implementation of informative CL-RRT for a UVMS using sequential quadratic programming as a numerical solver for (4) with $N = 5$ and step size $0.1\ s$. Suppose a vehicle navigates from an initial position $(r_{x,0}^v, r_{y,0}^v) = (0, 0)$ (magenta cross in the figure) at time $k = 0$ to a target object at $(s_x, s_y) = (0.9, 0.9)$ (magenta pentagram in the figure) in a domain $\mathcal{D} \in [0, 1.5]\ m \times [0, 1.5]\ m$. Starting from the initial position of the vehicle, the proposed CL-RRT grows a tree by sampling a new node and connecting it to an existing node. Compared to conventional RRT, CL-RRT connects two nodes using closed-loop predictions of a system which in our problem is computed by (4). In

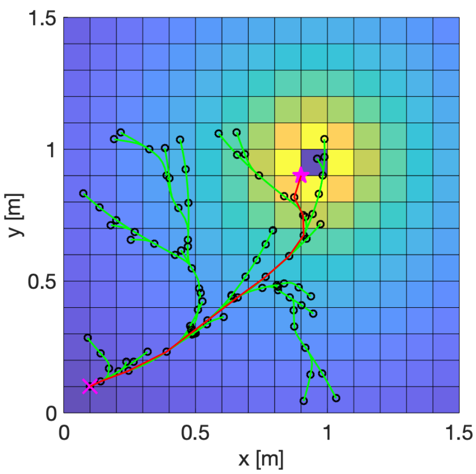

Fig. 1. Vehicle trajectories (green lines) with sampled nodes (black circles) generated by CL-RRT under development from the starting position (magenta cross) at (0,0) to the goal position (magenta pentagram) at (0.9,0.9). The red line represents the selected vehicle trajectory. Overlaid in the figure is an information map constructed by the log-determinant of the Fisher information matrix evaluated for the true object position.

the figure, nodes of the tree are shown as black circles and its branches between nodes as green lines. Once one or more branches of the tree reach the goal position, CL-RRT searches the most favorable trajectory connecting the initial position to the target position among others. In this example shown in the figure, only one trajectory shown as a red line is found. We can observe that the lines connecting nodes are sufficiently smooth to be dynamically feasible for a UVMS and a successful trajectory is generated from the initial position to the goal position. Overlaid in the figure is an information map constructed by the log-determinant of the Fisher information matrix evaluated for the true object position. Integration of this information map into CL-RRT is a work in progress. However, our current results show promise in the application of the CL-RRT and the Fisher Information matrix to this problem domain. In further work on this simplified problem, we will focus our future efforts to resolve identified challenges, including computational complexity in our MPC implementation associated with CL-RRT.

IV. Grasp Planning

In general, motion and grasp planning may operate in tandem to secure the object by planning not only vehicle motion, but also robotic arm motion. To facilitate our analysis, our preliminary work considers vehicle motion and robotic arm motion separately. In this section, we present potential frameworks for grasp planning we have identified. Once the UVMS has navigated near the object, the goal for retrieval tasks is to secure the object. However, object shape information may be incomplete due to limited visual coverage of the object along the approach trajectory caused by adverse visual conditions. Thus, it is necessary to not only identify end effector configurations that can securely grasp

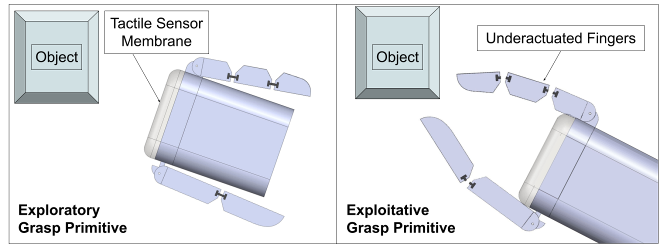

Fig. 2. Grasp primitives for underactuated hand. In the exploratory primitive (left), the fingers splay back to expose the membrane of an optical tactile sensor in the gripper palm for tactile exploration. In an exploitative primitive (right), the fingers close inward to secure the object.

the object, but also to identify configurations that explore the object with tactile sensors to gather information about object shape: so-called "exploratory" or "exploitative" grasp configurations, respectively [16].

Grasp configurations are commonly expressed as sets of contact points on the object surface [14]. However, because the gripper used in this project is underactuated, we express grasp configurations as tuples $g = \{\mathbf{v}, p\}$ consisting of an approach vector, $\mathbf{v}$, in the object frame and a *grasp primitive*, $p \in P$, where P is a set of primitive grasp configurations compatible with the underactuated gripper. A grasp primitive encodes the finger configuration, such as spherically or cylindrically wrapping, before grasping [17]. One of the grasp primitives available on the gripper is *tactile probing*, in which the fingers are splayed backward to expose an optical tactile sensor [18]. By pressing the sensor into the object, the UVMS can explore to learn the object's shape as shown in Fig. 2. We have defined grasp planning broadly to include exploratory grasping actions.

Exploratory grasp planning is enabled by previous algorithms to plan probing or grasping actions that reduce the uncertainty of object shape or pose [16], [19], [20]. Let us consider object shape only here and denote the belief in the shape of an object by B. Let $\mathcal{G}$ be the set of all kinematically reachable grasps $g = \{\mathbf{v}, p\}$. An exploratory grasp planner seeks to find $g^\star \in \mathcal{G}$ such that

$$g^\star = \underset{g \in \mathcal{G}}{\operatorname{argmax}} \; I_{\text{grasp}}(g|B), \tag{7}$$

where $I_{\text{grasp}}(g|B)$ is a function representing the information quality gathered by performing the grasp g given the belief B. $I_{\text{grasp}}(g|B)$ may be approximated with the Fisher metric from (6), or other metrics such as the reduction in Gaussian process variance resulting from achieving grasp g, given the most-likely observation outcome of achieving grasp g.

Exploitative grasps, which seek to secure the object for manipulation, are commonly generated with analytic grasp synthesis tools such as *GraspIt!* [21] or data-driven tools such as Dex-Net [22]. Exploitative grasp planners seek to find $g^\star \in \mathcal{G}$ such that

$$g^\star = \underset{g \in \mathcal{G}}{\operatorname{argmax}} \; L(g|B), \tag{8}$$

where $L(g|B)$ is the likelihood that a grasp g will successfully secure an object given the current belief B in the object's shape. The likelihood may be estimated with analytical metrics, by examining the proportion of grasps near g resulting in force closure, or by using a data-driven technique without explicitly modeling grasp metrics, as in Dex-Net. State-of-the-art methods have achieved high performance at identifying $g^\star$ for pick-and-place tasks on industrial robot arms.

Despite the strong performance of exploitative and exploratory grasp planners in terrestrial robot domains, the underwater environment introduces challenges to sensing and actuation that require algorithms that can gracefully accommodate adverse conditions. The underwater visual environment, which is characterized by turbidity, unpredictable shadows and reflections, and inconsistent lighting [23], degrades the performance of visual object recognition systems that are vital for grasp planning. The unconstrained motion of the freefloating UVMS base introduces uncertainty in the position of tactile sensors that impairs the performance of exploratory grasp planners. Additionally, uncertainty in underwater vehicle dynamics causes grasping actions to be less repeatable than in structured environments where grasp plans can be executed open loop.

The unique adverse conditions of the underwater environment motivate the decision to use an underactuated gripper with an optical tactile sensor. Underactuated grippers, which can securely grasp objects without precisely aligning individual fingers, provide robustness to actuation noise and localization uncertainty. An optical tactile sensor providing high-resolution depth images of the object's surface, as well as estimates of normal and shear force distributions, should enable robust operation-by-feel in turbid environments.

To address the sensing and actuation uncertainties caused by the underwater environment, state-of-the-art grasp planning algorithms must be adapted to suit the underactuated gripper and optical tactile sensor. First, a holistic object reconstruction scheme must be developed to fuse information from visual and tactile sensors to enable grasp synthesis. Ideally, this scheme will jointly optimize over UVMS and object configuration spaces to determine the most likely system state despite uncertainty in the position of sensor measurements. Second, an exploratory grasp planner must be developed to enable information-seeking actions with the optical tactile sensor. For this task, a Gaussian process implicit surface is considered [16]. Third, an exploitative grasp planner must be adapted to suit the compliant underactuated gripper. The exploitative grasp planner may also address additional constraints from the underwater environment, such as restrictions on joint limits necessary to maintain stability. Ongoing research enables progress in these promising directions.

V. Simulation and Planning Libraries

An accurate underwater simulator that can simulate accurate hydrodynamics for the vehicle and arm is necessary for testing the algorithms proposed in the previous sections before deployments. To this end, we use the open source Project Dave simulation environment [24]. Built on UUV Simulator

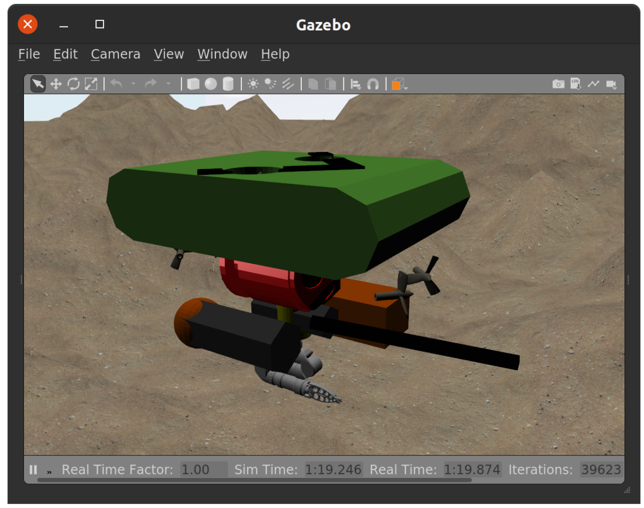

Fig. 3. The Seabotix vLBV300 and Blueprint Labs Reach Alpha Arm UVMS system in the Project Dave Simulator.

[25], Project Dave uses a ROS-based plugin system that implements Fossen's hydrodynamics model for underwater vehicles [26] inside of the Gazebo simulator.

Our system is composed of a Seabotix vLBV300 vehicle and a Blueprint Labs Reach Alpha 4 arm. The Seabotix vLBV300 is a four degrees-of-freedom tethered underwater vehicle with a range of 300 m with a mass of 22.2 kg that is neutrally buoyant. The Blueprint Labs Reach Alpha 4 arm is a four degrees-of-freedom arm made for underwater missions with a mass of 1.36 kg. The project team has procured both the vehicle and arm and is planning on performing hardware experiments using this system. Before deploying on hardware, it is prudent to test controls and planning algorithms in simulation first. Therefore, we extended Project Dave with models of both the vehicle and the manipulator arm (Fig. 3). Sensor modules for our simulated vehicle are still under development.

We have also incorporated the MoveIt! motion planning library [27] into the simulation pipeline. Within MoveIt!, we follow a similar approach as [28] where we represent displacements in the x, y, and z directions using prismatic joints and yaw using a revolute joint. Note that the Seabotix vLBV300 vehicle is neutrally buoyant and has negligible pitch and roll control in practice. Using MoveIt!, we can generate plans for the vehicle and manipulator system using standard kinematic motion planning algorithms included with the Open Motion Planning Library [29] such as RRT-Connect [30] and RRT* [31].

VI. Discussion

In this work, we have discussed our current progress in active motion planning for a UVMS. We have developed a simulation framework, conducted preliminary algorithm development for informative motion planning, and identified potential frameworks for exploitative and exploratory grasping with an underactuated hand and a tactile sensor.

During the deployment of our system, there is a need for the grasp planner to interact with the motion planner; as information is collected about the object through informative path planning, the grasp planner will update the target position for grasping the object, thus requiring replanning. The interplay between the motion planning and grasp planning frameworks is an area that we aim to explore as the project develops.

Another problem we will encounter during the deployment of our system is the coupling between vehicle motion and robotic arm motion due to hydrodynamics. For example, the motion of a manipulator may affect the motion of a vehicle, and vice versa. This coupling may cause some kinematically reachable grasps to fail during execution if the grasp results in an unstable UVMS configuration. Tightly integrating the motion planning and grasp planning frameworks can ensure that navigable trajectories ending in feasible grasp configurations can be continually refined while information is gathered throughout the approach. Additionally, a whole-body controller currently being developed by Intelligent Machines and Materials Lab at Oregon State University for the RSA project will play a key role in reducing the effect of arm-vehicle coupling on the UVMS.

The next steps of this project are to further develop and test these algorithms. We plan on testing first in simulation using the Project Dave simulator discussed in Section V. We will then deploy these algorithms on a mechatronic manipulator platform that is currently under development at the University of Washington's Applied Physics Lab. Ultimately, the techniques developed to address informative and adaptive motion planning and grasp planning will be vetted with a real-world deployment of our Seabotix Vehicle with the Reach Alpha 4 arm in an energetic ocean environment.

ACKNOWLEDGMENT

The authors would like to thank Natasha Troxler for sharing the illustration of the gripper used in this paper, and anonymous reviewers for providing valuable comments.

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