



# Autonomous Underwater Manipulation: Current Trends in Dynamics, Control, Planning, Perception, and Future Directions

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## Abstract

**Purpose of Review** Research in underwater manipulation has mostly focused on solving individual parts of the manipulation challenge; however, we believe a systemic approach needs to be taken to achieve full autonomy. With this survey, we aim to provide a review of the different dynamic modeling, control, motion planning, and perception methodologies presented in the literature, and, more importantly, we intend to highlight the necessary steps that need to be taken to achieve fully autonomous underwater manipulation.

**Recent Findings** Achieving autonomous manipulation in underwater environments is a complex and multi-disciplinary challenge. Recent works have focused on moving from simulation-based environments to experimental validation of the proposed methods. Furthermore, the advancements of machine learning have been making an impact in the underwater manipulation, data-driven strategies playing a central role in the last years developments.

**Summary** We present an overview of the current trends in the area of autonomous underwater manipulation. First, we provide a review of state-of-the-art algorithms developed in the area of dynamic modeling, control, motion planning, and perception. Second, we discuss the limitations of the current systems and present possible avenues to obtain robust autonomous manipulation.

**Keywords** Autonomy · Control · Perception · Dynamic modeling · Planning

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## Introduction

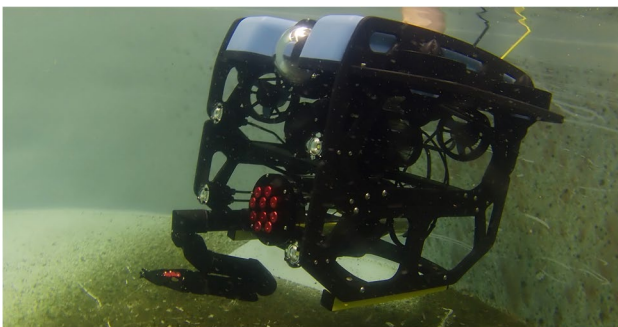
Underwater manipulation has become an important research topic, with applications ranging from subsea oil and gas [1], construction [2], military and archaeological intervention [3, 4], to deep sea specimen collection [5]. The majority of these applications rely on teleoperated systems [6] that have high operational costs, use large infrastructures, and require trained operators. To lower the burden of the operators, Ocean One [7, 8], an underwater humanoid robot, has been developed. One of the focuses of this system is the improvement of the human-robot interface for teleoperated underwater operations.

As highlighted in [9], there is a strong interest from various stakeholders to achieve autonomous underwater manipulation. Nevertheless, there are still many open challenges to enable underwater manipulators to perform autonomous intervention operations in a constantly changing environment. A truly autonomous underwater system should be able to complete a mission without human intervention; it should be able to cooperate with other autonomous agents, or with other humans, to achieve its objective. The development of

such a system requires many technological advancements and the integration of multiple systems.

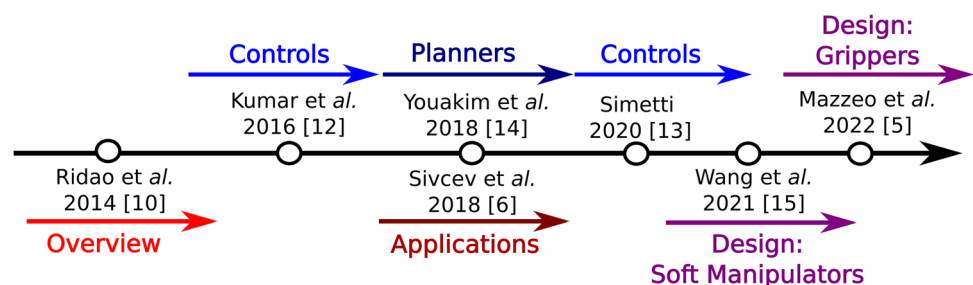
Research in the area of underwater manipulation is growing every year, with thousands of articles indexed in scientific search engines. These works have focused on various aspects such as manipulator and end-effector design, dynamic modeling, control strategies, motion and task planning, perception systems, or development of lightweight underwater vehicle-manipulator systems, as the one seen in Fig. 1. Although each of these areas presents explicit challenges that need to be solved independently, to obtain a fully autonomous system, there is a need for studies that look at designing these aspects in a more coordinated and coherent approach.

An overview of survey papers addressing these challenges is seen in Fig. 2. An initial survey [10] gives a timeline for all funded underwater intervention projects. More recently, Aldhaheri et al. [11] provided an updated overview of funded European projects focused on underwater manipulation discussing the limiting factors of these. In [12] the authors present an overview of control systems for underwater manipulation, briefly addressing the modeling aspect of the problem. A discussion of common control systems is also introduced in [13], focusing on both the type of tasks executed and testing environment. The most common algorithms for manipulator motion planning are given in [14]. A detailed survey of types of underwater manipulators that are commercially available and their application for industry are



**Fig. 1** Lightweight underwater vehicle-manipulator system: the Reach 5 Alpha manipulator mounted on a modified Bluerov2 Heavy robot

**Fig. 2** Overview of the surveys done in underwater manipulation. There have been observed three avenues: (1) algorithm development, the focus has been on control and planning, (2) overview and applications, and (3) mechanical design of new manipulators and end-effectors



presented in [6]. Flexible and soft robots used in underwater environments are described in [15], while [5] discusses the design of grippers focusing on deep sea collection. A special case of underactuated, compliant, tendon-driven robotic hands for deep sea exploration is presented in [8]. These surveys provide useful insights into specific parts of the underwater manipulation problem, but they fail to address how these aspects come together to enable robust and long-term manipulation. With this review paper we go a step further, by identifying what the critical aspects are in the robust and long-term autonomy, and discuss the design of informed and interconnected components.

The main contributions of this survey are to (1) identify the depending areas that facilitate underwater manipulation, (2) provide a description of the methods utilized for solving each of the identified areas, and (3) discuss the necessary steps to achieve fully autonomous underwater manipulation.

## Contributing Research Areas

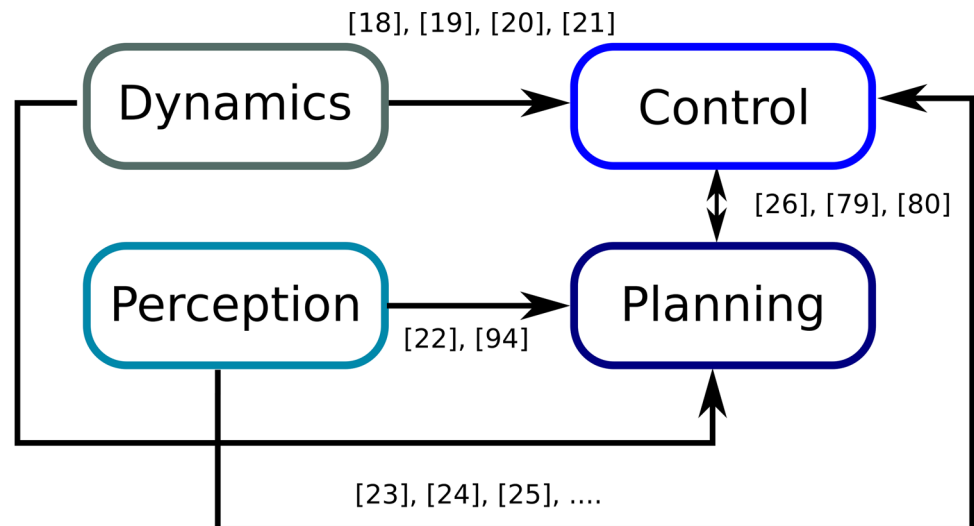
The IEEE Robotics & Automation Society states that mobile manipulation requires autonomous solutions from the field of sensor fusion, control, planning, perception, and machine learning [16]. Additionally, for mobile manipulators that operate in underwater environments, understanding the dynamics of the system is part of obtaining robust autonomy. A diagram showing the dependencies among these areas is presented in Fig. 3, highlighting several works that studied two or more aspects as part of the autonomous underwater manipulation research area.

## Dynamics

Mathematical models of robotic systems have proven to be a central part of validating and designing control systems [17]. However, achieving a reasonable level of accuracy is challenging for articulated multi-body systems operating in underwater environments. This is due to assumptions made for the mechanical design of the system and the hydrodynamic effects.

Physics-based approaches are the main methods that make such assumptions. The dynamic study of a manipulator

**Fig. 3** Dependencies between areas that facilitate underwater manipulation autonomy as discussed in several articles: [18–26], etc



in a fluid environment is introduced in [27], which proposes an approximation approach to obtain the generalized forces that act on the manipulator. The coefficients for the hydrodynamic forces are computed based on the geometry of the links, the generalized coordinates, and the relative position of the manipulator with respect to the surface of the fluid. In [28] and [18] the dynamic model for a two-link rigid manipulator is presented. The links are approximated as cylinders and the in-line hydrodynamic forces are modeled based on 2-D strip theory. This research shows how the drag and added mass forces coefficients can be defined as functions of the distance travelled, describing how the angle between consecutive links influences the hydrodynamic coefficients. Similar studies are introduced in [29] for a closed form dynamic model using Kane equations [30]. The method is demonstrated for a 3-degree-of-freedom (DOF) manipulator attached to a 5-DOF vehicle. Navier-Stokes equations and a Lagrange representation are used in [31] to model the dynamics of an underwater manipulator attached to a Remotely Operated Vehicle (ROV). The dynamic model of a planar manipulator with revolute joints attached to an Autonomous Underwater Vehicle (AUV) is presented in [19], using a Newton-Lagrange formulation. Disturbances such as currents or ripples are not considered in the model, but the dynamic coupling effects of the manipulator motion on the vehicle are incorporated in the model. The Composite Rigid Body (CRB) approach is presented in [20], obtaining the dynamic model of a lightweight underwater vehicle-manipulator system (UVMS) and providing an analytic method to estimate dynamic coupling effects. Lagrangian approaches are proposed in [32••] and [33] for a planar and a 3-DOF manipulator, respectively. Hyper-redundant manipulators, known as underwater swimming robots, are modeled in [34, 35], and [36]. The kinematic modeling aspects of these types of robots are presented based on redundancy

resolution. In [34] the results show how the hydrodynamic coefficients influence the behavior of the robot in a simulation environment. The works presented in [35] and [36] focus on using the dynamic model for the control system of the robot, without model validation.

Data-driven approaches for underwater manipulator dynamics have been created as an alternative to the analytical and physics-based approaches. Hydrodynamic modeling for underwater manipulators is introduced in [37] and [38]. Single-link manipulators with cylindrical and rectangular representations are considered for these studies. The necessary data is captured from sensors such as accelerometers, encoders, and optical sensors, while the manipulator is moving through water. In [37] 3D strip theory is used to determine the correlation between the added mass, drag coefficients, and the distance travelled by the manipulator. Experiments shown in [38] demonstrate that the added mass is not strongly dependent on the angular accelerations of the robotic manipulator. The dynamics of underwater manipulators are obtained in [39], using a feed-forward neural network based on joint velocity, but the accuracy of the obtained model is not validated.

In the past years, the areas of flexible and continuum underwater manipulators have gained attention. In [40] a cable-driven underwater manipulator is presented, where each section of the manipulator is controlled by a buoyancy adjustment unit. The dynamic analysis studies how the cable tension influences the motion of the manipulator and the buoyancy regulation system. In [21] a manipulator with one flexible link and one rigid link is discussed. To develop the equations of motion and corresponding boundary conditions, Hamilton's Principle is used. A Raleigh Beam representation is used for an underwater flexible manipulator in [41] and Bond graphs are leveraged to obtain the dynamic behavior of the system. Gümüsel and Özmen [21] states that

an Euler-Bernoulli flexible beam representation is the most common approach to describe flexible manipulators. This is confirmed in [42], where the system is modeled using the finite element method based on a Lagrangian approach. Similar methods are introduced in [43] and [44] to represent a biologically inspired continuum underwater robot from an octopus. Experimental validation demonstrates that, due to assumptions that are regularly made for underwater environments, the estimated model has some differences compared to the experimental results. Similar evaluation is presented in [45] where a flexible-link underwater manipulator is modeled using a recursive Gibbs-Appell formulation. In-air and underwater experimental validation are performed and it was observed that the deformation of flexible links and the rigid-body motion decrease due to the fluid-arm interaction. Data-driven models have also been used for the modeling of flexible robots. In [46] a system identification technique is presented based on parametric modeling using meta-heuristic algorithms such as cuckoo search and flower pollination, while [47] presents a recurrent neural network for the development of the dynamic model. Similarly, in [48], a deep neural network is used to compute the inverse kinematics of a rigid-flexible manipulator.

An overview of the approaches and algorithms used to model underwater manipulators is presented in Table 1. The vast majority of approaches are designed using an Euler-Lagrange formulation and are validated through simulation work. Moreover, disturbances and payloads are not considered in the dynamics. Therefore, it should be the aim of future research to develop more robust algorithms that are applicable to a wide variety of environmental and payload considerations.

## Control

The need for control laws that provide desired performance in the presence of disturbances and uncertainties has led to intense interest in the development of control methods for underwater manipulators.

In [49], position control of single-link underwater robot using a Proportional Integral Derivative (PID) controller is

investigated without considering the dynamic modeling. In [50] a cascaded Proportional Integral (PI) controller with an inverse dynamic feed-forward component is used for a two-link manipulator attached to an underwater vehicle. In [51] a kinematics-based controller for an UVMS is presented, that uses a decoupled control architecture of the vehicle and manipulator. Furthermore, a combination of task-priority redundancy resolution and task concurrence approaches, without any complex hydrodynamic model are investigated. Similarly, a decoupled kinematic control law is compared with a fully coupled control architecture for UVMS in [52]. The experimental results show the potential of the kinematic control laws in maintaining a certain end-effector configuration in an environment that has currents. These results are confirmed in [53], which presents a decentralized task-priority kinematic control algorithm for two UVMS collaboratively manipulating an underwater pipe. A soft manipulator arm is attached on a legged robot in [54]. The paper discusses the inverse kinematics control architecture of the manipulators collecting objects in confined spaces. Simulation results for a flexible underwater manipulator controlled by fuzzy logic are presented in [55]. For fully known system dynamics, a fuzzy logic controller can be designed for effective robust operation. In [56] a robust single input fuzzy logic controller (RSIFLC) scheme is successfully applied for task-space trajectory control of a simulated UVMS. The benefits of this controller have been shown by comparison to a feedback linearization proportional controller. The experimental evaluation of the feedback control of a 11 DOFs UVMS is presented in [57]. An adaptive model-based controller and a PID control architecture have been compared for the UVMS, showing similar behaviors for the cruise phase. An adaptive robust control strategy, known as active disturbance rejection control (ADRC) is shown in [58], successfully maneuvering a manipulator while compensating for dynamic coupling effects. In the absence of the precise analytical description of the system, the ADRC uses nonlinear state error feedback to estimate disturbances online with a state observer. In [58] a disturbance observer is used to regulate a manipulator attached to an ROV. A similar observer is proposed in [59]. In combination with a sliding

**Table 1** Dynamic model algorithms, where EL is Euler-Lagrange, NE is Newton-Euler, KM is Kane's Method, BG is Bond Graph, GA is the Gibbs-Appell formulation, ML is Machine Learning approaches, DF is Data Fitting

Properties	Methods						
	EL	NE	KM	BG	GA	ML	DF
Single-link manipulators		[27]				[47]	[37, 38]
Multiple body representation	[31, 32••, 33, 42, 43]	[20, 40]	[28, 29]	[41]	[45]	[39]	
Disturbances and payloads							
Simulation validations	[31, 32••, 33, 42]	[20, 27, 40]	[29]	[41]	[37, 45]	[46]	
Experimental validation	[32••]	[43]	[28]				[37, 38]

mode controller, this controller is capable of compensating for external disturbances and ensuring that the manipulator completes the task in a finite amount of time. A combined controller-observer scheme is designed in [60] for a vehicle-manipulator system. The observer is used to estimate the system's velocities in a model-based control formulation.

In [61] Sliding Mode Control (SMC) is applied to demonstrate the behavior of the underwater manipulator when tracking a predefined trajectory and handling a variable payload. A saturation function is introduced to solve the problem of chattering. A double-loop fractional integral sliding mode control (DLFISMC) is presented in [62] for trajectory tracking of an underwater manipulator with bounded external disturbance. The results show high-precision trajectory tracking performance and strong capability of disturbance rejection. An integral sliding mode controller is proposed in [63] in the context of parallel position-force control for an underwater manipulator in contact with the environment. Experimental results with an electric manipulator in contact with rigid and compliant environments show the benefit of such method.

Machine learning algorithms, specifically Neural Network (NN) and Reinforcement Learning (RL), have gained recognition in underwater robotics. Such approaches have been able to identify nonlinear system parameters and result in reliable behaviors. In [64] a Deep Reinforcement Learning (DRL) based on visual information is used for the control of a dual manipulator system mounted on a ROV. Through simulations, the benefits of such an approach for three DOF manipulators are presented. A DRL controller based on the deterministic policy gradient algorithm was developed in [65]. The controller was evaluated in simulation on a four DOF manipulator and showed benefits for working under position and torque constraints. In [66], reinforcement learning is used for adjusting the feed-forward prediction model of a soft manipulator for grasping applications in underwater environments. In [67••], a NN is used to estimate the dynamics of a manipulator and incorporate them into an adaptive Model Predictive Control (MPC) controller. This system has been used in an experimental set-up for a four-link manipulator and demonstrated how it can account for changes in the dynamics made by variable payloads. Similarly, the dynamics are incorporated into the control system for an underwater robotic manipulator using an adaptive NN in [68]. The optimal parameters of the controller have been obtained using Genetic Algorithms, and the behavior of the system for trajectory tracking has been evaluated through simulations. Imitation learning is used in [69] for an UVMS tasked to open underwater valves. Dynamic movement primitives are used to encode the UVMS trajectories and their efficiency is shown through tests performed in a water tank.

The majority of the papers discussed above have been focused on trajectory tracking or motion control, with a few

exceptions (see [63]). Nevertheless, the interaction with the environment and corresponding control structures have been also studied. In [70] a force/position tracking control for an UVMS in contact with a compliant environment is proposed. Direct force and position regulation control laws are leveraged in a cascaded architecture and the performance of the system is presented through simulations and experimental results. A MPC controller is developed in the framework of force/position control for an underwater manipulator system in [71], with active force and position control laws. Stability analysis using Lyapunov functions and simulation results present the benefits of this approach.

The above referenced papers are a few examples of methods used for control in underwater manipulators. A more detailed review of these approaches can be seen in [12, 13].

## Planning

Planning in the context of autonomous underwater manipulation is considered a complex problem due to the high dimensionality and lack of environmental structure. The dynamic nature of the underwater environment necessitates that planning methods be able to adapt to things such as moving obstacles, and to be able to handle uncertainties in the workspace and localization.

A review of common approaches used in motion planning is given in [72]. An analysis of most common approaches used in underwater manipulation planning is presented in [14], where three categories are tested: (1) sampling-based [73], (2) optimization-based [74, 75], and (3) search-based [76]. Simulation results are presented for both unobstructed and cluttered environments, as well as manipulation through a narrow passage. It is shown that sample-based planners outperform search-based and optimization-based motion planners in both planning time and path length for unobstructed environments. Nevertheless, for overall performance, it is concluded that non-optimal sampling-based techniques work well for time-critical applications, but at the cost of smoothness and path length. It is also shown that search heuristic-based planners are able to produce optimal trajectories with more natural motion and higher consistency, but often require more parameter tweaking.

Current planning methods are primarily focused on robot kinematics and function under the assumption that the environment is known, but motion planning in real-world environments can include a high degree of uncertainty. The work in [77] presents an adaptive planning method using a closed-loop rapidly exploring random tree algorithm, and provides a simulation framework for testing active control and planning algorithms in a dynamic environment. Another search-based planner, Multirepresentation - Multiheuristic A\*, is demonstrated in [78••], where an underwater manipulator succeeds to complete a valve-turning intervention in a water tank, in



a previously unknown environment. In [79] an autonomous docking planner is presented in the context of intervention AUVs. The paper is primarily focused on scheduling the tasks to be performed, leveraging both sonar and camera systems. A motion state planning architecture is presented in [80] for an UVMS based on adaptive tracking differentiator framework. This approach is shown to be beneficial for high-dimensional underwater systems that have difficulties in tracking fast changing trajectories, such as step signals.

Machine learning approaches have been shown to also be viable for vehicle path planning. An improved path planning algorithm capable of dealing with localization uncertainty is proposed in [81], where reinforcement learning is used to find an optimal path in GPS-denied scenarios with noisy measurement data. This type of approach could be extended to work with a UVMS.

## Perception

The perception system plays an essential role in achieving autonomous underwater manipulation [13, 82]. Its importance for applications where underwater interaction is needed has been highlighted in [23] stating that perception represents a major pillar for offshore robotic applications. Furthermore, [83] highlights the importance of having coordinated control and sensing strategies for the advancement of autonomy in the UVMS context.

The focus of the following paragraphs is on perception systems designed specifically for underwater manipulation tasks. One of the first papers that have looked at the idea of coordinating the perception system with the action of the underwater robotic system is [24], discussing the integration of reactive intelligence in ROVs. Several works have focused on the design of new perception systems, centered around optical cameras, lasers, or sonars. Among these, in [22] a stereoscopic telepresence vision system is presented for the enhancement of underwater intervention. The work describes the integration of optical cameras with a pan and tilt system that allows for higher coverage of the environment. A multi-camera system is designed in [84] and used with visual markers for underwater intervention. The camera uses a CCD sensor with good capabilities for low light conditions, similar with the optical cameras used in [85, 86]. Furthermore, [84] also focuses on the study of various algorithms for object detection, recognition, and 3D mapping for dexterous underwater manipulation. Libraries such as OctoMap [87] and methods such as active contours based on superellipse fitting [88] are used to achieve these goals. A stereo vision system is designed in [25] for pipe manipulation. The focus of the system is object pose estimation and localization. Algorithms such as the Sobel gradient operator, and perspective geometry concepts are used to solve these problems. In [89] an ORB feature detector is

incorporated to detect an object of interest based on template matching, where the perception system is used to design intuitive learning by demonstration methods. A convolution neural network (CNN) is presented in [90] to estimate the pose of targets. A fish-eye camera is used due to its capability to cover large areas without a decrease of the imaging sensor footprint. A visual servoing strategy is introduced in [91]. The visual information, obtained from a stereo camera system based on edge detection algorithms, is presented to control the motion of an underwater manipulator. In [92], a monocular camera is used for an image-based visual servoing control. The focus is on designing a distortion model that enables online camera calibration and compensates for inaccuracies in the image-tracking caused by the deflection of light rays passing through different mediums. A monocular camera is also used for grasping objects in [93]; however, the object detection is done by means of a CNN architecture. A vision-based feedback control using inverse kinematics is presented in [94] for UVMS. The paper uses the Single-shot MultiBox Detector (SSMD) with a kernelized correlation filter for the detection and tracking of underwater targets, when a binocular camera system is mounted on the vehicle and an on-hand monocular camera is mounted on the manipulator. The importance of camera calibration in perception for manipulation is also mentioned in [95]. This paper presents a visual servoing system for hydraulic underwater manipulation. A set of fiducial markers are used to establish the pose of the target. Fiducial markers have proven their applicability and robustness for object detection and localization, being used in [4] for detecting tools for autonomous underwater soil sampling.

Nevertheless, some of the approaches discussed above assume that the target always has either specific characteristics known a priori and/or labels that can be mounted in advance on the target. Some of these limitations have been addressed by developing object recognition and pose estimation using laser systems.

In [96] a fast laser scanner is used to build 3D colorless point clouds for autonomous underwater intervention in man-made structures. The proposed architecture uses segmentation algorithms, template matching approaches, and designs characteristic descriptors. This information represents the central aspect of a semantic Extended Kalman Filter (EKF)-based Simultaneous Localization and Mapping (SLAM). 3D reconstructions using multi-view laser approaches in the framework of underwater manipulation are presented in [97] and [98]. Laser peak detection and triangulation algorithms, demonstrated experimentally, are used to obtain the 3D reconstructions. Experimental results are also discussed in [99] for facilitating several grasping strategies based on the 3D reconstructions obtained with the multi-view laser. A laser combined with a camera system is used in [100] for object detection and recognition. The

approach presented combines a machine learning algorithm to detect the target in color images, while the laser information is used to obtain the depth information.

Although sonar systems are widely used for localization and scene reconstruction in underwater environments [101, 102], they have been used significantly less in the context of underwater manipulation, due to limitations such as high noise levels, loss of texture information, and lack of color information [103, 104]. To address some of these challenges, a physics-based simulator of a multibeam sonar is presented in [105] specifically for autonomous underwater manipulation. In [106] a simulated multibeam sonar imaging system is used to detect targets and to define the trajectory of an underwater manipulator.

## Future Work

While previous works focused on specific aspects of the manipulation problem, we argue that a manipulator system capable of autonomous intervention requires more than designing state-of-the-art algorithms.

Specifically, we consider that autonomy needs a degree of reasoning, a few examples being to infer from the environment where it operates, to act accordingly to its own state, or to account for out of distribution cases. This leads to the need of a deeper interaction between the components of the system, including a high-level decision making component.

In human intelligence, our brain creates models based on our perceptions [107], humans are capable of making long-term predictions, but also, of acting instinctively and performing fast reflexive behaviors [108]. This is a clear demonstration of how human senses, actions, and planning capabilities come together for making us effective in our day to day lives. Similarly, we could ensure that underwater manipulators can be autonomous and effective if we design informed and interconnected components.

Taking the example of mathematical models presented in Section 2.1, several aspects can be well represented by analytical formulations (e.g., coupling effects and restoring forces), while others would require data-driven formulation to obtain reliable representations (added mass and drag coefficients). Nevertheless, these two types of modeling techniques can be combined to obtain semi-parametric models, leveraging known analytical models with information obtained through direct real-world experience. Other aspects that need to be addressed in the underwater modeling domain for manipulator systems, are considerations towards dynamic payloads (as seen from Table 1), coupling effects between manipulators, or proper characterization of hydrodynamic effects regardless of the body of water where they operate. Solving such problems could play a huge impact

in obtaining better simulation environments and designing digital twin systems.

Obtaining dynamic models through experience highlights the importance of perceiving accurately the environment where the system operates. Furthermore, perception systems are essential in guaranteeing that the underwater manipulation task is feasible. Optical perception modules in underwater systems face specific difficulties, such as low light scenarios, backscattering, or wavelength attenuation. Laser systems have limited spectrum range that they can effectively operate underwater, while sonar systems suffer from lack of texture and details in the obtained data. Restricted field of view and slow computation are some of the specific limitations for perception systems in the underwater manipulation context. Further developments in the design of novel sensors and computational approaches are needed to address these challenges. Efforts should also be made to reduce the gap between simulated and real environments which will allow for faster knowledge transfer and will facilitate the adoption of underwater robotic systems [109]. Furthermore, for underwater manipulators with eye-in-hand configurations [110], small footprint perception system must be designed.

Accurate perception of the world can facilitate the making of optimal decisions. Low level control systems can leverage the manipulator models and the observations of the environment to achieve optimal behaviors. As the vast majority of underwater manipulators are attached to a vehicle, the control system needs to ensure there is coordination between the vehicle and manipulator, be resilient to disturbances, and produce robust and feasible behaviors. Development of model-based adaptive control strategies that are easily transferable among various underwater manipulators and capable of operating in various conditions should be designed. Developments in machine learning, such as reinforcement learning, can be leveraged to obtain optimal controllers; however, emphasis on safety needs to be a central part for such methods. Furthermore, more attention should be given to interaction control structures, as the purpose of underwater manipulators is to interact with the environment. From Section 2.2, it can be seen that only a few works have focused on theoretical and experimental validation of the proposed control system, and even less papers have deployed the system in real-world conditions such as open waters.

The control and perception systems are essential parts in the design of effective motion planning algorithms for autonomous underwater manipulation. For example, information regarding the design of the control system can influence how close the waypoints generated by the motion planning system have to be to avoid overshoot. A more obvious example is how the perception system needs to identify obstacles, for the planner to ensure obstacle avoidance capabilities. Moreover, lower computational real-time motion planners

should be designed to enable reactive on the fly behaviors and re-planning capabilities for underwater manipulators. One other aspect that needs to be considered in the motion and interaction planning framework is the design of planners that coordinate the motion of the vehicle and the manipulator either in centralized or decentralized frameworks.

Finally, all of these subsystems need to directly interact with a hierarchical reasoning component, which is one of the systems which presents the highest difficulty. Previous research has shown different degrees of success in solving the control, perception and modeling issues; however, reasoning is still largely unresolved. RL is a suitable candidate for solving the problem by direct interactions with the environment, with the RL agent having a higher ranking in the hierarchy when interacting with other subsystems. By maximizing a simple reward function, RL agents have been able to solve extremely complex problems [111]. However, RL has several issues: large amounts of data are required for learning [112], models are not easily transferable, agents do not give information on why specific actions are selected, and more importantly, some argue that simple scalar rewards are not enough to achieve general intelligence [113]. Current alternatives in the literature are limited, but new developments in the field of neuroscience have shown that induction learning can be used to learn from few experiences to solve a wide range of tasks in an explainable way [114]. Another possibility is the development of multi-objective RL techniques. These types of intelligent agents utilize a multi-objective reward function, which can improve safety and explainability [113].

On top of these theoretical developments, one major aspect that we consider essential to ensure that autonomous underwater manipulation reaches the maturity similar to land and aerial robots is to have systems that are affordable and widely available. This requires a transition towards small electrical vehicle-manipulator systems, as the ones described in [115]. However, current autonomous UVMS systems are limited by the capacity of their batteries, which reduces their autonomy, requiring frequent recall of the system to the surface for battery replacement or recharge. One solution to this problem would be the development of alternative in situ charging stations. Some preliminary studies have been done in [116]. Furthermore, efforts should also be made towards the development of components that are both energy and computational efficient. This can extend the mission duration, and operative range, while saving time, resources and limiting carbon emissions. Another important step that can be made towards the progress and wide adoption of autonomous underwater manipulators is the development and active maintenance of simulators and open-source software-hardware architectures. Such tools would allow users to rapidly prototype and develop new algorithms, lowering entry cost. However, such efforts must be done by the community at large.

## Conclusion

This survey presents the state-of-the-art work done in the field of dynamic modeling, control, motion planning, and perception in the context of underwater manipulation. In the past years, significant research has been done in these areas, contributing towards the maturity of autonomous underwater intervention. Data-driven and physics-based modeling tools have been designed, adaptive force/position control architectures have been studied, and optical and laser systems have been used for visual perception systems. Search-based, sample-based, and optimization-based motion planning techniques have been applied for underwater intervention.

In this paper, we discuss the interconnections between modeling, control, perception, and planning, and the importance of designing approaches that consider these dependencies. To achieve the same level of autonomy for underwater manipulation that terrestrial and aerial systems have, it is important to understand how the individual components influence each other, and create architectures that actively consider this aspect.

Lastly, we want to stress the importance of open-source software and hardware. Having open access to designs, and the ability to collaborate, can facilitate the advancement of new technology in the domain of autonomous underwater intervention, and can accelerate deployment to various industries. It can also serve to increase affordability and access to underwater technology.

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## Declarations

**Conflict of Interest** The authors declare that they have no conflict of interest.

**Human and Animal Rights and Informed Consent** This article does not contain any studies with human or animal subjects performed by any of the authors.

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Papers of particular interest, published recently, have been highlighted as:

### ●● Of major importance

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