Machine Learning and Dynamic Whole Body Control for Underwater Manipulation

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Abstract Autonomous underwater manipulation is still nowadays an open research challenge. This paper describes the approaches to tackle some of the open challenges. On the one side, the use of machine learning techniques for the online identification and adaption of vehicle dynamics (dealing with drift compensation, mass changes, etc) as well as the use of high-level context-based configuration of controllers to adapt to changes in system morphology, hardware, and/or tasks. On the other side, a robust control of underwater manipulators based on an extension of whole-body control techniques is envisaged which takes into account the heterogeneous actuation (thrusters on the base, actuators on the arm joints) as well as the uncertain underwater vehicle dynamics. The result is a highly-reconfigurable system than can automatically adapt its behaviour to cope with changes in the environment, in its own morphology and/or in the task goals. The outcomes are planned to be validated in two different scenarios: a floating-base dynamics testbed originating from space applications and aerial robots at DLR and an underwater pool at DFKI.

1 Introduction

Manipulators mounted on commercial and research underwater vehicles are predominantly remotely teleoperated. The open challenges impeding autonomous operation are mostly coming from two sources: on the one side, one problem is the uncertainty and complexity in the models (both vehicle and hydrodynamics models). This chal-

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lenge affects as well the control of the underwater vehicle, but it is especially critical for the performance and control of a manipulator mounted on such an underwater vehicle, particularly due to the dynamic coupling of forces between manipulator and vehicle (e.g. the manipulator's motion and contact forces 'disturb' the vehicle's motion and vice versa). The second challenge comes from the underactuation of the vehicle (usually equipped with less actuators than degrees of freedom to be controlled). The fact that underwater vehicles are underactuated becomes more prominent and critical the moment a manipulator is mounted on the vehicle, which requires higher dexterity and precision. And this challenge has two effects: first, the impossibility to generate arbitrary trajectories to reach a desired point in space brings the needs for more complex trajectories and nonlinear control techniques and, secondly, the use of poor performance 'slow' thrusters compared to the 'faster' actuators employed in the manipulator requires a robust control architecture able to deal with this heterogeneous actuation system.

Currently, remotely operated manipulators are standard equipment for most ROVs, while on the contrary autonomous manipulation is still a research challenge and very few examples of the latest are available (one such example is the work in [18]). In principle, the equations of motion of underwater manipulators are similar to the equations of fixed manipulators. However, there exists some crucial differences such as the uncertainty in the model knowledge (mainly due to the poor knowledge about the hydrodynamic effects), the complexity of the mathematical model, the kinematic redundancy of the system (vehicle plus arm), the difficulty in controlling the vehicle in hovering (mainly due to poor thruster performance) and the dynamic coupling between the vehicle and the manipulator.

Control of floating manipulation structures was the focus of research since the 1980s, especially in the field of space robotics, leading to important results in hierarchical control architectures. With regard to the underwater domain, initial work was carried out in the 1990s in the control of a manipulator [23] and the problem of coordination between vehicle and arm control for teleoperation [16]. One of the first successful attempts at underwater autonomous manipulation were made within the SAUVIM (Semi Autonomous Underwater Vehicle for Intervention Mission, University of Hawaii) project also in the late 1990s [26]. Since the first works, a key aspect have been the exploitation of redundancy through some kind of task-priority framework and this is also the main focus of the recent work in [18]. Here, a control framework is presented to develop a multipurpose Intervention Autonomous Underwater Vehicle (I-AUV) including a 7-DOF manipulator arm within the TRIDENT EU FP7. In particular, the work focuses on the exploitation of the highly redundant system for achieving a dexterous object grasping. A survey on the developed control architectures for underwater robots up until the late 1990s can be found in [25].

In recent years, holistic approaches to control robotic systems as a whole have appeared which are known as 'whole-body control' techniques, especially for complex and highly-redundant systems composed of a mobile platform (either wheels or legs) and a manipulation system. These whole-body control frameworks take care of multiple and simultaneous control objectives (posture control, manipulation, walking, etc). Since whole-body control uses real-time feedback, robots using those approaches are more adaptive and can react promptly to unexpected sensory feedback signals, resolving at runtime for the optimal use of the all available robot degrees of freedom. The origins of whole-body motion generation is found on the generation of walking on humanoid robots while trying to ensure balance of the system.

In [17], the term 'whole-body control' was used for the first time to refer to a floating-base task-oriented dynamic control and prioritization framework that enables a humanoid robot to fulfill simultaneous real-time control objectives. Prioritization and coordination of several controllers is achieved using a hierarchy that handles conflicts and selects the one with highest priority. As soon as manipulation comes into play and, consequently, the contact with the environment is desired and not treated as a disturbance, complex robotic systems need to deal with simultaneous multi-contact forces (feet and mobile base with the ground, manipulator or manipulators with the objects being manipulated), and with the task of keeping balance or an optimal posture, among others. This requires efficient and online control strategies based on real-time feedback which can make optimal usage of the redundancy of such robotic systems. This is not only relevant for humanoids, but also in applications in which we have highly-redundant systems, for instance dual-arm robotic systems that need to cope with simultaneous tasks [4]. Given the nature of a free-floating system such as those composed of an AUV and a manipulator, it seems suitable to use the concepts of whole-body control for the underwater domain, especially when manipulation actions (and thus, contact forces) come in to play. However, there are challenges to be faced in this new domain, such as the heterogeneous nature of the actuation, the automatic reconfiguration based on current context or tasks, and dealing with the dynamics effects previously mentioned.

The next sections will provide some details of the methods to be used to deal with those challenges.

2 Methods

2.1 Machine Learning for Context-Adaption and Automatic Reconfiguration of Whole-Body Control Tasks

As previously mentioned, one of the predominant challenges in underwater manipulation arises from the complex and nonlinear interaction between the manipulator's body and its surrounding fluid. Nonlinearities in the dynamics arise naturally due to several hydrodynamic effects such as added mass, damping and lift effect, buoyancy due to Archimedes as well as external disturbances [6]. Precise estimation of hydrodynamic parameters is nearly impossible due to variations in the environmental parameters such as temperature, water density and salinity [1]. Classical modeling techniques of the hydrodynamics of such submersibles suffer from inaccuracies due to the simplification of the mathematical equations, i.e., assuming geometrical symmetries of the body and neglecting the effects of high order nonlinearities. In this manner, machine learning appeals as a promising technique for learning complex nonlinear models provided their inputs and outputs, and can therefore account for unmodeled aspects of the vehicle's hydrodynamics [21]. In the case of a free-floating manipulation such as the one mounted on an AUV, it is of utmost relevance to be able to perform high precision manipulation actions. This process gets even more complex when the manipulator has to handle objects which different shapes and sizes, which renders any pre-programmed hydrodynamic equations obsolete. As a result, two challenges at hand can be seen, where the first is developing a model that provides accurate predictions and with an estimated uncertainty of these predictions that can be used for navigation purposes. The second challenge is faced when the dynamics of the robot change (for example carrying a different weight or parts of the robot's body has been changed). Here is when online learning comes into play to adapt the dynamics model by learning the dynamics in real-time from the stream of data extracted form the robot's sensor suite. Consequently, the first task is to deal with the development of a software library using machine learning techniques to experimentally identify the dynamic motion models of the vehicle-arm system and adapt these models accordingly with different manipulation tasks, as well as to incorporate those models into the whole-body control framework. In this regard, DFKI has been using online model identification techniques based on machine learning to identify motion models of underwater vehicles (in this case, without manipulator) [9], [22] and [20]. Similarly, there are experiences in experimental identification of robot dynamics using classical techniques and machine learning approaches [2], or using data-driven methods for dynamics identification [24]. Those methods could be used to augment the information from the simulations models with experimental data.

Figure 1 depicts the concepts behind these developments. On the top, the challenges: the environmental disturbances and the load changes or hardware reconfiguration desired in a modular multipurpose unterwater manipulator. The goal envisioned would be to achieve a persistent operation, that is, long-term autonomy by accurate and adaptive dynamics estimation. Finally, the methodology is based on using machine learning techniques for identifying the system dynamics by using experimental data and online learning to cope with changing dynamics.

Finally, one of the main hurdles of whole-body controllers is that their configuration is a tedious task, which is usually done by hand given a certain system and/or task. For this reason, the development of automatic strategies to configure the parameters of the whole-body controllers given high-level contextual and task information using machine learning techniques is a key requirement to succeed on their practical usage. Moreover, the required controllers need to be also automatically selected and configured given the different hardware modules selected to build a specific system. In turn, the configuration information can be used as prior knowledge for modelling and adapting the system dynamics. Thus, the result is a system than can adapt its behaviour using contextual information as well as changes the morphology of the software control nextwork using information about the hardware.

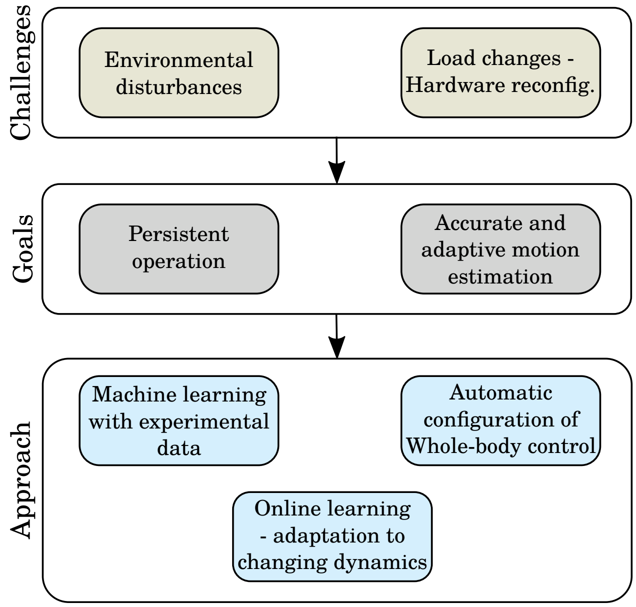

Fig. 1 Conceptual idea of the challenges, goals and approach followed for the whole-body system dynamics identification using machine learning techniques

2.2 Extension of Whole-Body Control for Underactuated and Heterogeneous Systems

The application of underwater robots with actuated base and articulated arms requires to combine mobility and manipulation skills. Consequently, whole-body control approaches, which allow to integrate multiple control objectives with different priorities, have been proposed for this class of systems [1]. In the context of physical interaction a hierarchical compliance control framework was proposed in [15] for fixed base manipulators using passivity arguments. The combination of such compliance controllers with a position/velocity controlled mobile base was considered in [5]. Moreover, the same framework has also been appied to the floating base dynamics of a legged robot, but under the assumption that the available contacts allow a proper control of the contact forces [10]. In order to apply similar control approaches to underwater manipulators, we can utilize a structural similarity between different robot systems with floating base dynamics. When comparing the main rigid body dynamics in space manipulators [8], legged robots [7], as well as aerial manipulators [11], one can observe a common dynamic structure in which the foating base dynamics is used in combination with different contact conditions and different actuator properties. In the context of underwater manipulators, in particular the vehicle underwater dynamics and the possibly underactuated control system of the vehicle play impotant roles. For the controller design, particular attention has to be put on the robustness of the controller with respect to uncertainties in the underwater dynamics. The theoretical robustness analysis can be based on the concept of input-state-stability and can take usage of a system formulation in which the model uncertainty is considered as a disturbance of the nominal controlled dynamics. The redundancy of the complete kinematic chain allows to consider different task variables including vehicle pose and momentum variables at different priorities in the control hierarchy. In fact, the use of the total system's momentum variables instead of the vehicle pose and orientation recently has led to efficient controllers in the context of space robotics [8] and it is very likely that similar properties can be also utilized in underwater systems. Furthermore, one of the fundamental challenges will be the question how to cope with the dynamic interaction between the (required) contact forces for manipulation and the possibly underacted dynamics of the base.

Based on a general hierarchic framework for controlling underactuated underwater manipulators, the next challenge is the extension of this framework towards more realistic actuator models and control architectures appearing in underwater systems. The thrusters of the underwater vehicle have relatively slow dynamics and control rates as compared to state-of-the art robot manipulators. Moreover, also distributed computing for the base and the manipulator needs to the considered. Therefore, one finally has to cope with a heterogeneous control architecture in which different subsystems and sensors are operated at different control rates. The Time Domain Passivity concept (TDPC) presents a powerful framework for such heterogeneous control architectures. The final goal is a generic controller design methodology which can isolate the effects of time delays, sampling, and actuator dynamics on the overall performance. As a first step towards this goal, the TDPC can generate additional corrective control components to improve the robustness of the overall whole-body controllers against these model imperfections.

3 Evaluation

The control strategies developed are planned to be tested and evaluated in two different testbeds. On the one side, the core whole-body control developments will be initially validated in an existing floating-base dynamics simulation infrastructure for space applications and flying robots located at DLR (see Fig. 2(right)). In parallel, the whole-body system dynamics will be validated at the underwater pool at DFKI (see Fig. 2(left)). At a later stage, the final developments will be validated as well at the underwater pool at DFKI, using the available underwater manipulators at DFKI.

Model learning often requires sufficiently rich data that have to cover most of the model's state space, as it is nearly impossible to cover the full space [14]. Therefore, acquiring large and rich datasets is an essential step for learning accurate models. For such purposes, identification experiments will be carried out extensively at the maritime testing facility at DFKI, where additional excitation of the system would be

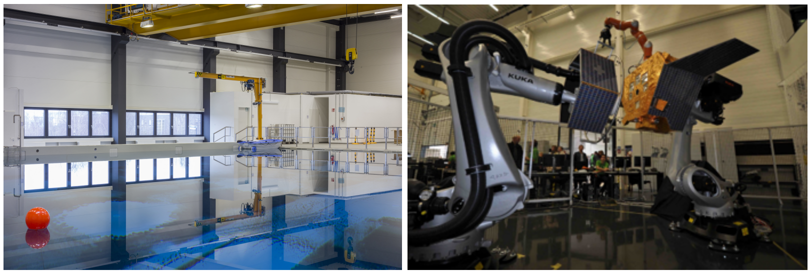

Fig. 2 *left:* Pool for testing underwater vehicles located at DFKI, *right:* floating-base dynamics simulation infrastructure for space applications and flying robots located at DLR

required. For example, the robot would be commanded to traverse random-periodic trajectories. Several methods that can be utilized to generate such trajectories are discussed in more details in [19]. To ensure good generalization of the models, separate experiments have to be conducted for testing the model's performance. Validation experiments would typically involve commanding the robot to perform random point-to-point trajectories, and thereafter cross-validate the model prediction with the measured data. This methodology has been tested using two AUVs (without a manipulator) at DFKI, where comparisons between several machine learning methods and classical physics-based methods were presented in [21, 22].

For the on-line learning approach, data stream need to be acquired and processed incremental and in real-time. In such situations additional methods for adding and forgetting samples are required to deal with the continuous flow of data. As the robot will physically interact with its environment, it is required to account for unknown or unforeseen situations it might encounter. Therefore, experimental trials that involve time-dependent dynamics are required. Several experimental scenarios can be designed, where it is required from the robot to perform tasks that are not accounted for previously, such as interacting with different objects of unknown masses, or following a certain trajectory while equipped with different payloads, etc. Such experiments are necessary to test and validate the capability of the on-line learning to continuously adapt to new situations. Other than the prediction accuracy of the learned models, two additional aspects to be tested are respectively, (1) the speed of adaptation, and (2) the model's capability to switch between previously learned contexts or decide if a new model needs to be learned. A concept framework of online learning of AUV dynamics was presented in [20], where we provide methods adding and forgetting data samples as well as an outliers rejection method. The framework was validated on experimental data from an AUV with a modification in its mechanical construction.

Additionally, few approaches can be used to improve the overall performance of on-line learning. One idea is the use of combine learning with expert knowledge which can be used as prior information to the learning method, [13]. Another approach is increasing the speed of convergence of on-line learning by choosing appropriately the set of data samples, this approach is usually referred to as *active learning* [3, 12].

The robotics hardware in the loop simulator Fig. 2(right) has been applied in the past to the evaluation of various floating base systems including free-floating space manipulators and aerial manipulators based on helicopters. Applying this system to the development and evaluation of control approaches for underwater manipulation requires to implement a representative approximation for the underwater effects in the vehicle dynamics. One of the advantages of this system is the fact that various different situations for the vehicle dynamics (i.e. different underwater effects in e.g. stationary or dynamic fluid) can be emulated with small effort. Also, it allows to separate the effects of the robot's own dynamics and the effects of the environment in which the robot is acting. The tests performed on this system will focus on the use of momentum variables for the whole-body control under different emulated underwater conditions. These tests are considered as a preliminary evaluation before performing outdoor field tests in a real underwater environment.

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