

Data-driven controllers and the need for perception systems in underwater manipulation

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Abstract—The underwater environment poses a complex problem for developing autonomous capabilities for Underwater Vehicle Manipulator Systems (UVMSs). The modeling of UVMSs is a complicated and costly process due to the highly nonlinear dynamics and the presence of unknown hydrodynamical effects. This is aggravated in tasks where the manipulation of objects is necessary, as this may not only introduce external disturbances that can lead to a fast degradation of the control system performance, but also requires the coordinating with a vision system for the correct grasping and operation of the object. In this article, we introduce a control strategy for UVMSs working with unknown payloads. The proposed control strategy is based on a data-driven optimal controller. We present a number of experimental results showing the benefits of the proposed strategy. Furthermore, we include a discussion regarding the visual perception requirements for the UVMS in order to achieve full autonomy in underwater manipulation tasks of unknown payloads.

I. INTRODUCTION

Currently, there are increasing efforts to explore and exploit maritime resources to further expand and advance capabilities within the oil & gas industry, research, and military applications. However, many of these underwater applications consist of intervention tasks in which dexterous manipulation is required [1]. Usually, a Remotely Operated Vehicle (ROV) will perform these tasks where an underwater manipulator is attached to a vehicle, and a human operator is in charge of driving the system. This approach involves high operational costs due to the need of specialized operators and large infrastructures. An alternative solution is the use of fully autonomous systems [2], [3], where a manipulator is mounted on an Autonomous Underwater Vehicle (AUV). With these systems, underwater manipulators can perform autonomous tasks in any underwater environment [4]. A key stepping-stone in developing fully autonomous capabilities for manipulators on board AUVs is implementing robust control structures and active perception systems. This is challenging as these

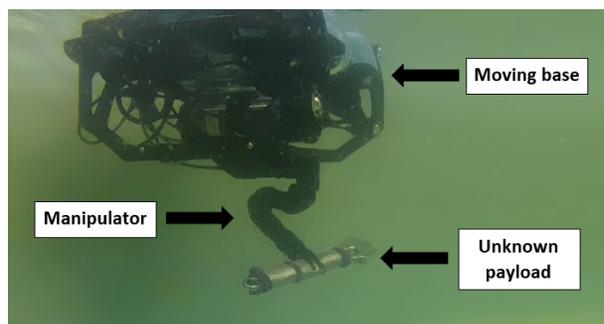


Fig. 1: The underwater manipulator Reach Alpha 5 is mounted on the BlueROV2 Heavy and has a wrench as payload.

systems are high-dimensional, highly nonlinear, governed by parametric uncertainties, have limited power supply, and they have to act robustly in environments with very poor visibility [5].

Underwater intervention tasks usually require interaction with the environment and manipulation of payloads that might be unknown a priori. For instance, some tasks may require the underwater manipulator system to carry or transfer some payload, or to use specialized tools for maintenance/repair applications [6]. This increases the difficulty of the manipulation problem as the system has to correctly localize and grasp these objects. Furthermore, once these objects have been grasped the behavior of the manipulator system is now affected by the dynamics of the objects. In addition, information about the possible payloads may be unknown which further increases the problem's complexity [7]. In search of complete autonomy for the manipulation of unknown payloads in underwater environments, there is an express need of having a reliable perception system but at the same time a control system robust to changes and capable of performing complex operations is required. However, this problem has not been extensively studied in the literature [8]. While the paper starts by presenting the control architecture for UVMS, Fig. 1, working with such unknown payloads, it also provides a detailed discussion about the perception system needed to achieve high accuracy underwater manipulation autonomously.

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II. UNDERWATER MANIPULATOR DYNAMICS

The dynamic model of an underwater manipulator is given by the equation of motion, as follows:

$$M(\mathbf{q})\ddot{\mathbf{q}} + C(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + D(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \eta(\mathbf{q}) + f_f(\mathbf{q}) = \boldsymbol{\tau} - J^T F \quad (1)$$

where $\boldsymbol{\tau} \in \mathbb{R}^n$ are the torques of the manipulator joints, and n is the number of joints of the manipulator, $\mathbf{q} \in \mathbb{R}^n$ are the joint positions, $\dot{\mathbf{q}} \in \mathbb{R}^n$ represent the joint velocities, and $\ddot{\mathbf{q}} \in \mathbb{R}^n$ are the joint accelerations, with n being the number of joints. On the left side of the equation, we have the inertial matrix $M(\mathbf{q}) \in \mathbb{R}^{n \times n}$, the Coriolis and centripetal vector $C(\mathbf{q}, \dot{\mathbf{q}}) \in \mathbb{R}^n$, the damping and lift vector $D(\mathbf{q}, \dot{\mathbf{q}}) \in \mathbb{R}^n$, the restoring forces vector $\eta(\mathbf{q}) \in \mathbb{R}^n$, and the friction vector $f_f(\mathbf{q}) \in \mathbb{R}^n$ [9], [10]. On the right side, the vector of interaction forces with the environment is represented as $F \in \mathbb{R}^6$ with $J \in \mathbb{R}^6$ being the Jacobian of the manipulator [11].

While some parameters in the model presented in Eq. (1) can be easily obtained, others, such as those related to hydrodynamic effects, can be difficult to obtain [12]. Consequently, simplifications are usually made about certain parameters while obtaining the model. Furthermore, learning the information of the environmental forces requires force/torque sensors, which can be costly, especially for deep-sea applications. While it is possible to estimate the interaction force vector using current measurements from the manipulator, they tend to have a high degree of uncertainty [13].

An alternative to classical modeling comes from data-driven techniques. In these formulations, a black box type function is obtained that relates the input forces of the system, $\boldsymbol{\tau}$, with the resulting position and velocities [14]. Under such formulations, artificial neural networks or Gaussian processes are used to learn the dynamics of the system [15]. The advantage of this type of modeling is that the model learns the true interaction without any simplifications to the model. Under such models, the dynamics of the system can be written as:

$$[\mathbf{q}_{t+1}, \dot{\mathbf{q}}_{t+1}] = \mathbf{g}(\mathbf{q}_t, \dot{\mathbf{q}}_t, \boldsymbol{\tau}_t | \boldsymbol{\theta}) \quad (2)$$

where \mathbf{g} is the Neural Network (NN) function and $\boldsymbol{\theta}$ are the parameters of the network. Through this technique, obtaining the robotic system's model becomes the task of finding the NN parameters that best describe the relationship of the input data to the output data [16].

While data-driven techniques may provide an improvement over classical modeling, some problems still persist. Changes between the training and testing configuration of the manipulator is one of the limitations of data-driven models. For example, if in the testing phase the robot will have to manipulate unknown payloads, this can cause discrepancies between the NN model obtained during training phase and the one used in the testing

phase. These changes need to be taken into account within the model or a loss of accuracy occurs, which may cause a performance degradation. However, in order to do so, it would be necessary to have information about the objects a priori, which is not always possible. Furthermore, when working with small manipulators, such as the one in this article, the weight of payloads may be comparable to the actual size of the manipulator. For example, the Reach 5 Alpha manipulator weights only 1.3 kilograms but can lift up to 2 kilograms underwater.

Therefore, when working with unknown payloads, data-driven techniques are not enough to ensure the desired working conditions will be met. In the following sections, we will develop an adaptive formulation within the context of optimal control that together with the data-driven modeling approach shows promising results for the control of underwater manipulators.

III. CONTROL SYSTEM FOR UNDERWATER MANIPULATORS

In this section, we will describe the main components of our proposed algorithm, the Neural-Network Model Predictive Control (NNMPC) controller. The basic control system structure can be seen in Fig. 2. Our control system is based on a two layer architecture. In the lower layer (Data-Driven Model Predictive Control), we have a data-driven Model Predictive Control (MPC) controller, namely the NNMPC. This controller uses a data-driven model based on a neural network. The controller receives the current state of the system ($\dot{\mathbf{q}}_t$ and \mathbf{q}_t) and a desired reference ($\mathbf{r}_t^{\dot{\mathbf{q}}}$ and $\mathbf{r}_t^{\mathbf{q}}$), and outputs the optimal action (\mathbf{u}_t) that will bring the arm to the desired reference state. In the following paragraphs, we introduce the lower layer of the controller.

A. Data-Driven Model Predictive Control

The MPC control approach focuses on minimizing a cost function over a finite horizon window. This minimization takes into consideration any constraints imposed on the system, such as the joint limits of the manipulator and the dynamic model of the system. In this project, we define a cost function in the context of MPC, as:

$$J(t) = P(t) \sum_{t_0}^t \mathbf{e}_t \Delta l + \sum_t^{t+N} \|\mathbf{r}_t^{\mathbf{q}} - \mathbf{q}_t\|_{Q_1(t)}^2 + \|\mathbf{r}_t^{\dot{\mathbf{q}}} - \dot{\mathbf{q}}_t\|_{Q_2(t)}^2 + \|\Delta \mathbf{u}_t\|_{R(t)}^2 \quad (3)$$

where $\mathbf{e}_t \in \mathbb{R}^n$ is the integral error in position with $\Delta l \in \mathbb{R}$ being the integration step, $\mathbf{r}_t^{\mathbf{q}} \in \mathbb{R}^n$ and $\mathbf{r}_t^{\dot{\mathbf{q}}} \in \mathbb{R}^n$ are the position and velocity references, $\mathbf{q}_t \in \mathbb{R}^n$ and $\dot{\mathbf{q}}_t \in \mathbb{R}^n$ are the position and velocity states, $\mathbf{u}_t \in \mathbb{R}^n$ is the torque commands sent to the arm, and $\Delta \mathbf{u}_t \in \mathbb{R}^n$ is the variation between commands sent at time t and $t - 1$. Additionally, $R(t) \in \mathbb{R}^{n \times n}$, $Q_1(t) \in \mathbb{R}^{n \times n}$,

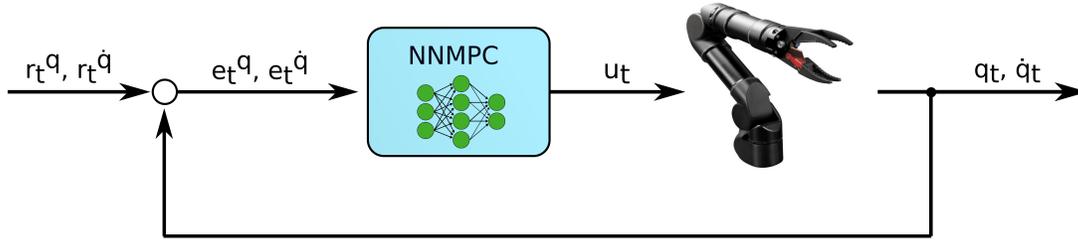


Fig. 2: Basic structure of the proposed NN MPC controller. The NN MPC takes as input the error between the current state of the system ($\dot{\mathbf{q}}_t$ and \mathbf{q}_t) and the desired reference ($\mathbf{r}_t^{\mathbf{q}}$ and $\dot{\mathbf{r}}_t^{\mathbf{q}}$) and outputs the control commands to the arm (\mathbf{u}_t).

$Q_2(t) \in \mathbb{R}^{n \times n}$ and $P(t) \in \mathbb{R}^{n \times n}$ are the weight matrices, and N is the horizon window for which the problem is being solved. Notice that we make all the weight matrices ($R(t)$, $Q_1(t)$, $Q_2(t)$, $P(t)$) dependent on time, which means that these matrices can be modified depending on the current state of the system at time t .

In the classical MPC formulation, the future states of the system, $\mathbf{s}_{t+1} = [\mathbf{q}_{t+1}, \dot{\mathbf{q}}_{t+1}]$ to $\mathbf{s}_{t+N} = [\mathbf{q}_{t+N}, \dot{\mathbf{q}}_{t+N}]$, are typically predicted using a linear model of the plant being controlled. In our case, however, we are interested in developing a data-driven formulation using neural networks. Under this scenario, we consider a neural network that will predict the successive states of the system as:

$$[\Delta \mathbf{q}_{t+1}, \Delta \dot{\mathbf{q}}_{t+1}] = \mathbf{g}(\mathbf{q}_t, \dot{\mathbf{q}}_t, \mathbf{u}_t | \boldsymbol{\theta}) \quad (4)$$

where $\mathbf{g}(\cdot) \in \mathbb{R}^{3n} \rightarrow \mathbb{R}^{2n}$ is the neural network function, $\boldsymbol{\theta}$ are the parameters of the NN, $\Delta \mathbf{q}_{t+1} \in \mathbb{R}^n$ is the change in position, and $\Delta \dot{\mathbf{q}}_{t+1} \in \mathbb{R}^n$ is change in velocity. With this formulation, instead of directly learning the successive state of the system, we learn the change with respect to the previous state [14]. The successive state can then be obtained by a simple operation, i.e., $\mathbf{q}_{t+1} = \mathbf{q}_t + \Delta \mathbf{q}_{t+1}$.

With this formulation in mind, the MPC control formulation can be written in the following way:

$$\begin{aligned} \mathbf{u}^*(t) = \min_{\mathbf{u}_{t+l}} & P(t) \sum_{t_0}^t \mathbf{e}_t \Delta t + \sum_t^{t+N} \|\mathbf{r}_t^{\mathbf{q}} - \mathbf{q}_t\|_{Q_1(t)}^2 \\ & + \|\mathbf{r}_t^{\dot{\mathbf{q}}} - \dot{\mathbf{q}}_t\|_{Q_2(t)}^2 + \|\Delta \mathbf{u}_t\|_{R(t)}^2 \quad (5) \\ \text{subject to} & \quad \mathbf{u}_{t+l} \in \mathbb{U}^n \\ & \quad \mathbf{q}_{t+l} \in \mathbb{X}^n \\ & \quad \forall t = 0, \dots, N \end{aligned}$$

where the optimal action ($\mathbf{u}^*(t)$) is obtained by minimizing the cost function $J(t)$ in Eq. (3), and the position and velocity at time t are obtained using the NN formulation previously described in Eq. (4).

Although the data-driven formulation provides advantages in comparison to the classical MPC, large variations in the dynamics of the system can create problems where the data-driven approach may not be able to ensure the control requirements are met. Under such cases, it may be necessary to re-tune the parameters of the control system to adjust to the changing dynamics, as one set of tuning parameters may not be enough for every working condition. This brings the need for an adaptation mechanism that allows the weights of the MPC to be modified on-line.

IV. CONTROLLER EVALUATION

The controller presented in the previous section has been deployed on the Reach Alpha 5 underwater manipulator [17] capable of working in depths of up to 300m. This manipulator has five degree-of-freedom (DOFs) consisting of four rotating joints and one end-effector gripper. However, we are not interested in controlling the gripper so for the remainder of the results section we will be working with the first four DOF. We consider the case of the arm moving once the unknown payload was already grabbed by the arm, so a vision system for detecting the object was not incorporated. We utilize Robot Operating System (ROS) to communicate with the manipulator at a frequency of 20Hz.

The data-driven NN model of the manipulator was developed using Tensorflow. The employed artificial neural network was a fully connected feed forward net with two hidden layers of 25 neurons each. The input to the neural network is a vector of size 12 consisting of the positions (\mathbf{q}_t), velocities ($\dot{\mathbf{q}}_t$) and actions (\mathbf{u}_t). The net provides the estimated successive state at time $t+1$. The data for training the network was obtained with real-time data, by performing random motions with the manipulator. The activation functions used for the hidden layers are *ReLU* [18], while a *tanh* function is used in the output layer. In the implementation of the NN, we utilized the Mean Squared Error Loss (MSE) function,

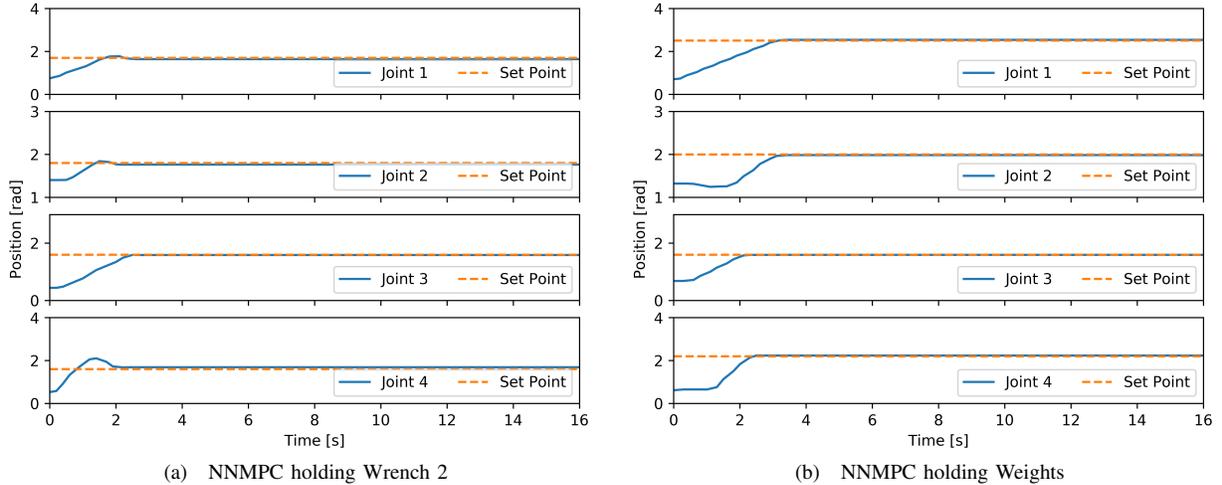


Fig. 3: NN MPC controller on moving base holding different weights. a) Holding the wrench with $\mathbf{r}_t = [1.7, 1.8, 1.6, 1.6]$ radians. b) Holding weights with $\mathbf{r}_t = [1.7, 1.8, 1.6, 1.6]$ radians

which has an equation $L(\theta) = \sum_i^N (s_i - \hat{y}_i)^2$. The training of the neural network was performed using the Adam optimizer, a gradient based optimization algorithm [19] available in the Tensorflow library. Additionally, we used a learning rate of $lr = 0.001$.

The cost function used for all experiments is that of Eq. (3). To solve the MPC optimization problem, we used the Python library pyOpt [20], and we utilized the Constrained Optimization BY Linear Approximation (COBYLA) algorithm [21]. We set an horizon window of $N = 7$ with a sampling rate of $dt = 0.05$ seconds.

The tests were performed in a cylindrical water tank with a depth of 1.5 meters and a diameter of 2.5 meters. In these tests, we are interested in the performance of the algorithm when the arm is manipulating a variety of objects. We show results for two different objects, each with different characteristics, that the arm has to hold with the gripper while trying to reach the desired joint positions. Information about the weight and geometry of the objects was unavailable to the control systems at all times, and therefore these objects are effectively unknown. Therefore, for the remainder of the paper we refer to these objects as unknown payloads. The payloads are: a wrench weighing 0.5 kg (wrench) and 12 inches long, and a set of weights packed together weighing 1 kg (weights) and three inches width and length and two inches height. However, when selecting the objects, the dry mass range of the payloads were restricted by the limitations of the Reach Alpha 5 manipulator, which has a lift capacity of 2kg [17]. The testing setup can be observed in Fig. 1.

In the first test, the arm was manipulating the wrench

while trying to reach a desired joint position of $\mathbf{r}_t = [1.7, 1.8, 1.6, 1.6]$ radians. The obtained joint positions are shown in Fig. 3a. It can be seen, that while the joint positions are reached in less than 3 seconds, joint 4 presents a small overshoot, which relates to the extra torque caused by wrench in the joint. Following, we performed a test with the arm holding the 1 kg weight. For this test, the desired joint position is $\mathbf{r}_t = [2.5, 2.0, 1.6, 2.2]$ radians, and the obtained results can be seen in Fig. 3b. We can see that due to the extreme characteristic of the payload, joints 2 and 4 require a longer time to reach the desired joint position.

V. PERCEPTION FOR UNDERWATER MANIPULATION

The preceding results show the advantages of data-driven modeling techniques. In this regard, the NN helps to capture unmodeled dynamics in the manipulator, which improves the overall performance of the controller. This process brings substantial performance improvements when facing unknown payloads. This is of great importance in furthering autonomous operations that require manipulation with unknown payloads.

Regarding the sensing techniques utilized, the Reach Alpha 5 is a high precision arm that utilizes encoders for obtaining the joint states. The arm uses magnetic off-axis position encoders (iC-MU from Haus integrated circuits) which have an accuracy of ± 0.1 degrees in the joint position. Those sensors are integrated inside the arm so the controller gets an immediate update with no interference. For our current implementation, the biggest concern with regard of sensing comes from the potential case in which one of the encoders fails. In such case,

the uncertainty in the measurements goes outside of the bounds given by the manufacturer and the controller will be unable to perform its required tasks.

Additionally, we only consider the case of the arm moving once the unknown payload was already grabbed by the arm, so a vision system for detecting the object was not implemented. However, this will be required for the whole system in the case of autonomous control. We theorize that a combination of 3D vision, utilizing cameras, together with underwater image restoration, would allow the UVMS to obtain the necessary visual feedback to close the perception-action cycle [22].

In this sense, stereo vision is a common way of controlling a robotic manipulator with camera feedback [23]. Typically, object detection is used to find the object that must be manipulated. Once the object is found, the next step is to find the distance to the object. This can be calculated using trigonometry by having two cameras that are a known distance apart from each other and both looking at the object [24]. This distance can then be sent to the control system to modify the required end-effector position based on the current payload location with respect to the UVMS [25].

However, one problem faced in underwater environments is the poor visibility, caused by the strong absorption and scattering effects [26]. Additionally, light changes and water turbidness can cause adverse effects on the image, distorting it and decreasing the clarity. One solution to this problem could be haze removal and color correction. Haze removal makes the output image clearer and rids much of the blurriness that occurs. Next, color correction is done to extract the true colors of the image. In underwater environments, the blue and green channels present higher intensities than the red channel [27]. Therefore, by performing color correction, the colors appear more vividly, as they would out of water, adding more detail to the image [28].

By combining these methods, we believe that the problem of unknown payload manipulation in UVMS could be solved autonomously. Two cameras could be used to give feedback to the controller and operate the arm correctly. Simultaneously, haze removal and color correction will modify the images from the camera to produce a more accurate representation of the underwater environment. However, in order to deploy this type of system completely autonomous, increased computational power is necessary. For this reason, we plan to increase the load capabilities of the UVMS by incorporating another enclosure, that will allow us to mount additional cameras, together with an additional computer. We plan to incorporate an NVIDIA Jetson nano, due to its small footprint and high computational power.

VI. CONCLUSIONS

In this work, we developed a low-level controller based on data-driven Model Predictive Control for the control of an underwater manipulator working with unknown payloads. We utilized a NN to derive a model for the manipulator which was used by the MPC controller. In this way, we were able to obtain a more accurate model of the manipulator that directly takes into consideration the environmental disturbances. While previous works have utilized such a formulation, most have been done in simulation or utilized the network to directly learn the commands of the MPC controller. We were able to solve the data-driven optimization problem online by utilizing a low impact NN. Moreover, we provide a discussion regarding the necessary steps for the creation of a perception system that will allow the UVMS to perform the unknown payload manipulation, in changing underwater environments, autonomously.

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