The Effect of Model Accuracy and Thruster Saturation on Tracking Performance of Model Based Controllers for Underwater Robotic Vehicles: Experimental Results

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Abstract

This paper reports an experimental investigation of the effect of two specific errors on a class of model based controllers for the low-speed maneuvering of fully actuated underwater vehicles. First, we review previously reported studies and a commonly accepted simplified plant model that has been experimentally validated for this class of vehicles. Second, we review a family of associated model-based nonlinear controllers — both fixed and adaptive — for trajectory tracking, as well as the commonly employed proportional-derivative (PD) controller. Third, we report an experimental evaluation of the performance of this entire family of controllers in the presence of two commonplace modelling errors: plant parameter mismatch, and thruster saturation. In the presence of plant model parameter errors, the fixed model based controllers often perform worse than PD control, and the adaptive controllers "learn" the correct parameters to provide asymptotically superior performance. In the presence of unmodelled thruster saturation, the adaptive controllers performs worst, and the model-based controllers perform no worse than PD. To the best of our knowledge, this is the first reported experimental evaluation of the effect of model-parameter error and thruster saturation on the effect of linear and model-based tracking controllers for underwater vehicles.

1 Introduction

This paper reports an experimental evaluation of the effects of model accuracy and thruster saturation on the tracking performance of a family of model based controllers for fully actuated underwater vehicles during low speed maneuvering. The controllers tested include a Model Based Exact Linearizing Controller (EL), a Model Based Nonlinear Controller (NL), an Adaptive Model Based Exact Linearizing controller (AEL), an Adaptive Model Based Nonlinear Controller (ANL), and a basic Proportional-Derivative (PD) controller. These controllers were designed to track a continuous position and velocity trajectory. The problem of trajectory tracking is defined as follows: Given the underwater vehicle dynamical plant model and a continuous bounded time varying reference trajectory, whose derivatives are continuous and bounded, design a thrust control law that ensures asymptotically exact tracking of the reference trajectory.

Model accuracy and thruster saturation directly effect the performance of model based controllers. If a controller is designed using a plant that does not accurately represent the actual physical plant, theoretical stability results will not apply to the *actual* system. Similarly, if an actuator such as a thruster saturates, the ideal dynamical plant model is violated, and the theoretical predictions regarding dynamic performance no longer apply to the actual plant.

All experiments were conducted using the Johns Hopkins University Remotely Operated underwater robotic Vehicle (JHU ROV). The experimental identification and validation of the decoupled, single degree of freedom dynamical plant model of the JHU ROV used in designing the model based controllers was reported in [21, 22, 23]

The paper is organized as follows, first we will present a brief literature review of model based control for underwater vehicles. Next we present the experimentally identified dynamical plant model for the JHU ROV. This is followed by the presentation of the PD, EL, NL, AEL, and ANL controllers in Section 3. Then in Section 4.1 we present the effect of model accuracy upon controller tracking performance and in Section 4.2 we report on the effect of thruster saturation on controller tracking performance.

1.1 A Brief Literature Review of Model Based Control of Underwater Vehicles

Finite-dimensional approximate plant models for the dynamics of underwater vehicles are structurally similar to the equations of motion for fully-actuated rigid body — both classes of plants are nonlinear, yet the plant parameters enter linearly into the overall nonlinear differential equation of motion. For the special case of second order mechanical systems with *linear* dynamics, classical linear controller design techniques apply directly. Early studies of trajectory tracking for nonlinear plant dynamics arising in rigid-body holonomic mechanical systems employed linearized plant approximations in order to apply linear control techniques [15, 8, 24].

A significant number of previously reported studies of the control of underwater vehicles employed linearized plant approximations both for the theoretically justified case of setpoint regulation and the theoretically unjustified case of trajectory tracking. In [11] the authors report a linear discrete-time approximation for vehicle dynamics, and report simulation of linear quadratic and robust control methods for this class of discrete time linear plants. In [12, 18] the authors report linear quadratic control and self tuning control of linearized plant models and numerical simulations. In [7, 16] the authors report PI and linear model-reference adaptive control of a linearized plant model and experimental demonstrations. In [13, 14] the authors report the model-reference adaptive control of a linearized plant models and numerical simulations. In [6] the authors report the sliding-mode control of a linearized plant models and numerical simulations.

A few studies, e.g. [17], have reported neural network and/or fuzzy logic control technique and numerical simulations. Numerous control studies demonstrate the performance of proposed closed-loop systems in computer simulations alone, e.g. [12, 6, 25, 1], or employ non-parametric control methodologies that do not require knowledge of the plant dynamics [5].

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Relatively few control studies directly address decoupled nonlinear plant models for underwater vehicles. In [27] the authors report nonlinear sliding mode control and numerical simulations for X, Y, and heading. In [5, 28, 3] the authors report on the experimental performance of a model-based adaptive controller for an underwater vehicle. The first experimental evaluation of nonlinear adaptive sliding-mode model based control on underwater vehicles was reported in [26].

In [4] the authors address the problem of model-based vehicle state estimation. Several reported studies address the special case of propulsion-less and appendage-less symmetric vehicles in inviscid fluid for which the partial differential equations governing the surrounding fluid has a closed form solution, e.g. [19].

Several studies address fully coupled nonlinear plant models, controllers, and report simulation studies, e.g. [9, 10, 2]. These approaches typically make explicit assumptions on the structure of the approximate finite-dimensional vehicle plant dynamics to ensure that the vehicle plant model possesses passivity properties identical to those possessed by rigid-body holonomic mechanical systems — an assumption that has not been empirically validated for real-world underwater vehicles.

2 Decoupled Single Degree of Freedom Dynamical Plant Model for the JHU ROV

The plant model employed in this study is an experimentally validated, decoupled, single degree of freedom dynamical plant model for the JHU ROV. The JHU ROV, Figure 1, is a tethered, remotely operated underwater robot. The position (x_1, x_2, and x_3) and heading (x_4) of the vehicle are actively controlled and the vehicle is passively stable in roll (x_6) and pitch (x_5). Vehicle x_1 and x_2 position were measured with a 300 kHz acoustic long baseline system. Depth was measured using a Paroscientific 8DP-700-1 Digiquartz depth sensor. Heading (x_4) was measured using a prototype Litton LN200 IMU. Roll and pitch (x_6 and x_5) were measured using a KVH Azimuth Digital Gyro Compass (ADGC). Five current-controlled, 1.5 kW DC brushless thrusters were used as actuators. The thrust control law was $i_c(t) = k_t^{-1}\tau(t)$. A detailed description of the JHU ROV is given is [20].

The dynamical plant model takes the form

$$\begin{aligned}\tau_i(t) \quad &= \quad m_i\dot{v}_i(t) + d_{Q_i}v_i(t)|v_i(t)| + d_{L_i}v_i(t) + b_i, \\ & \quad\quad m_i > 0;\ d_{L_i}, d_{Q_i} > 0, \end{aligned} \tag{1}$$

or, rewritten,

$$\begin{aligned}\dot{v}_i(t) \quad &= \quad m_i^{-1}\tau_i(t) - m_i^{-1}d_{Q_i}v_i(t)|v_i(t)| - \\ & \quad\quad m_i^{-1}d_{L_i}v_i(t) - m_i^{-1}b_i, \end{aligned} \tag{2}$$

where, for each degree of freedom (DOF) i, $\tau_i(t)$ is the net control force, m_i is the effective mass, $d_{Q_i}v_i(t)|v_i(t)|$ and $d_{L_i}v_i(t)$ represent the hydrodynamic drag, and b_i is the buoyancy.

This simple decoupled plant model has been experimentally validated and reported in [22], in which the authors report experimental identification of plant parameters, and compare the performance of the identified plant model to the experimentally observed dynamic response of the actual vehicle. In addition, the experimental setup and instrumentation employed is reported in [22]. The experimentally identified parameter values are listed in Table 2.

3 Model Based Control

In this section we present the basic Proportional-Derivative (PD) controller, the fixed model based controllers (EL and NL), and the adaptive model based controllers (AEL and ANL).

3.1 PD Controller

The basic PD controller takes the form

$$\begin{aligned}\tau(t) \quad &= \quad k_p\Delta x(t) + k_d\Delta v(t), \\ & \quad\quad k_p, k_d > 0, \end{aligned} \tag{3}$$

where k_p and k_d are scalar error feedback gains. The state error coordinates are defined as

$$\begin{aligned}\Delta x(t) &= x_d(t) - x(t), \\ \Delta v(t) &= v_d(t) - v(t), \\ \Delta\dot{v}(t) &= \dot{v}_d(t) - \dot{v}(t), \end{aligned} \tag{4}$$

where $\dot{v}_d(t)$, $v_d(t)$, and $x_d(t)$ are the desired acceleration, velocity, and position. Note that $v(t) = d(x(t))/dt$. In the case where the buoyancy term, b, is zero, the PD controller will perform setpoint regulation but not trajectory tracking.

3.2 Exact Linearizing Model Based Controller

The Exact Linearizing Model Based Controller (EL) takes the form

$$\begin{aligned}\tau(t) \quad &= \quad m\dot{v}_d(t) + d_Q v(t)|v(t)| + \\ & \quad\quad d_L v_d(t) + b + k_p\Delta x(t) + k_d\Delta v(t), \\ & \quad\quad m, k_p, k_d > 0,\ d_Q, d_L \geq 0, \end{aligned} \tag{5}$$

where m, d_Q, d_L, and b are known scalar quantities, $\tau(t)$ is the controller output, and k_p and k_d are PD scalar error feedback gains. The state error coordinates are defined in (4). The EL fixed model based controller provides asymptotically exact position and velocity trajectory tracking. In addition all signals remain bounded, as reported in [23].

3.3 Non-Linear Model Based Controller

The Non-Linear Model Based Controller (NL) takes the form

$$\begin{aligned}\tau(t) \quad &= \quad m\dot{v}_d(t) + d_Q v_d(t)|v_d(t)| + d_L v_d(t) + \\ & \quad\quad b + k_p\Delta x(t) + k_d\Delta v(t), \\ & \quad\quad m, k_p, k_d > 0,\ d_Q, d_L \geq 0, \end{aligned} \tag{6}$$

where m, d_Q, d_L, and b are known scalar quantities, $\tau(t)$ is the controller output, and k_p and k_d are PD scalar error feedback gains. The state error coordinates are defined in (4). The NL fixed model based controller provides stable position tracking and asymptotically exact velocity tracking. Additionally, all signals remain bounded, as reported in [23].

3.4 Adaptive Exact Linearizing Model Based Controller

The Adaptive Exact Linearizing Model Based Controller (AEL) takes the form

$$\begin{aligned}\tau(t) \quad &= \quad \hat{m}(t)\dot{v}_d(t) + \hat{d}_Q(t)v(t)|v(t)| + \\ & \quad\quad \hat{d}_L(t)v_d(t) + \hat{b}(t) + k_p\Delta x(t) + k_d\Delta v(t), \\ & \quad\quad k_p, k_d > 0, \end{aligned} \tag{7}$$

Table 1: Nomenclature

Degree of Freedom	Force Moment (Body Coord.)	Linear Velocity Angular Velocity (Body Coord.)	Linear Position Angular Position (World/Inertial Coord.)
1: X Translation (Surge)	$\tau_1(t)[N]$	$v_1(t)[m/s]$	$x_1(t)[m]$
2: Y Translation (Sway)	$\tau_2(t)[N]$	$v_2(t)[m/s]$	$x_2(t)[m]$
3: Z Translation (Heave)	$\tau_3(t)[N]$	$v_3(t)[m/s]$	$x_3(t)[m]$
4: Rotation About Z(Yaw/HDG)	$\tau_4(t)[N-m]$	$v_4(t)[rad/s]$	$x_4(t)[rad]$
5: Rotation About Y(Pitch)	$\tau_5(t)[N-m]$	$v_5(t)[rad/s]$	$x_5(t)[rad]$
6: Rotation About X(Roll)	$\tau_6(t)[N-m]$	$v_6(t)[rad/s]$	$x_6(t)[rad]$

Table 2: Dynamical Plant Model Parameters

Degree of Freedom	Inertia	D_Q	D_L	Buoyancy
1 (x_1)	266.3 [kg]	1173.4 [kg/m]	0 [kg/s]	-1.96 [N]
2 (x_2)	424.6 [kg]	2120.9 [kg/m]	0 [kg/s]	1.73 [N]
3 (x_3)	1603.3[kg]	1766.84[kg/m]	0 [kg/s]	-31.01 [N]
4 (x_4)	98.04 [(kg m^2)/rad]	187.1 [kg m^2]	0 [(kg m^2)/(rad s)]	0.1197 [N-m]

where $\hat{m}(t)$, $\hat{d}_Q(t)$, $\hat{d}_L(t)$, and $\hat{b}(t)$ are adaptive estimates of the scalar plant parameter values, $\tau(t)$ is the controller output, and k_p and k_d are PD scalar error feedback gains. The plant parameter error coordinates are defined as

$$\begin{aligned} \Delta m(t) &= \hat{m}(t) - m, \\ \Delta d_Q(t) &= \hat{d}_Q(t) - d_Q, \\ \Delta d_L(t) &= \hat{d}_L(t) - d_L, \\ \Delta b(t) &= \hat{b}(t) - b, \\ \Delta \Psi(t) &= \hat{\Psi}(t) - \Psi, \\ \Delta \dot{\Psi}(t) &= \dot{\hat{\Psi}}(t);\ \dot{\Psi} = 0, \end{aligned} \tag{8}$$

where $\hat{\Psi}(t) = [\hat{m}(t); \hat{d}_Q(t); \hat{d}_L(t); \hat{b}(t)]_{4\times1}$ is an estimate of the unknown plant parameter vector $\Psi = [m; d_Q; d_L; b]_{4\times1}$. The parameter update law is

$$\dot{\hat{\Psi}}(t)_{4\times1} = \Gamma X(t) \Delta v(t), \tag{9}$$

where $\Gamma_{4\times4} = diag[\gamma_i]$, for i= $1\cdots4$, with $\gamma_i \geq 0$, and $X(t) = [\dot{v}_d(t); v(t)|v(t)|; v_d(t); 1]_{4\times1}$. All signals remain bounded using the AEL controller. Further, asymptotically exact velocity tracking, and the asymptotic convergence of the time derivative of the adaptive parameter estimates to zero is reported for the AEL controller in [23].

3.5 Adaptive Non-Linear Model Based Controller

In this section the Adaptive Non-Linear Model Based Controller is presented. The ANL takes the form:

$$\begin{aligned} \tau(t) &= \hat{m}(t)\dot{v}_d(t) + \hat{d}_Q(t) v_d(t)|v_d(t)| + \\ &\quad \hat{d}_L(t) v_d(t) + \hat{b}(t) + k_p \Delta x(t) + k_d \Delta v(t), \\ &\quad k_p, k_d > 0, \end{aligned} \tag{10}$$

where $\hat{m}(t)$, $\hat{d}_Q(t)$, $\hat{d}_L(t)$, and $\hat{b}(t)$ are estimates of the scalar plant parameter values, $\tau(t)$ is the controller output, and k_p and k_d are PD scalar error feedback gains. The plant parameter error coordinates are defined in (8) and the state error coordinates are defined in (4).

The parameter update law is

$$\dot{\hat{\Psi}}(t)_{4\times1} = \Gamma X(t) \Delta v(t), \tag{11}$$

where $\Gamma_{4\times4} = diag[\gamma_i]$, for i= $1\cdots4$, with $\gamma_i \geq 0$, and $X(t) = [\dot{v}_d(t); v_d(t)|v_d(t)|; v_d(t); 1]_{4\times1}$. The ANL controller provides asymptotically exact velocity tracking and stable position tracking. Further, the time derivative of the adaptive parameter estimates asymptotically converges to zero and all signals remain bounded [23].

4 Experimental Results

In this section we present the experimentally investigated effect of model accuracy and thruster saturation on controller performance. All experiments were conducted using the JHU ROV. The PD (k_p and k_d) and adaptation gains (γ_i) were the same for all controllers during these experiments so as to provide a fair comparison of performance under similar conditions. Previously, simulated tracking performance of these controllers was reported in [23], and a preliminary experimental comparison of their tracking performance was reported in [22].

4.1 The Effect of "Bad" Model Parameters

How do "bad" model parameters effect the performance of the model based controllers? In was shown in [22] that the model based controllers perform better than a basic PD controlled when designed with "good" model parameters. To demonstrate what happens when a model based controller is designed based on "bad" model parameters, the JHU ROV was commanded to track a position and velocity reference trajectory using the NL model based controller using both "good" and "bad" model parameter values. The results were directly compared. The PD and EL controllers were also run for comparison, using "good" parameters. Despite not relying upon previously identified model parameter values, the AEL and ANL controllers were run for comparison as well. This test was run in the x_4 DOF. The PD gains were the same for all the controllers ($k_p = 250, k_d = 100$) and the trajectory tracked was of the same peak magnitude (0.436 radians) and frequency (0.785 rad/s).

The experimental results shown in Figure 2 clearly show that the use of "bad" model parameters in the NL model based controller severely degrades tracking performance. It is also clear that to graphically present and examine each position and velocity tracking plot for each trajectory in each DOF for the five controllers considered in this paper would be extremely cumbersome and impractical. As a result we have adopted a position

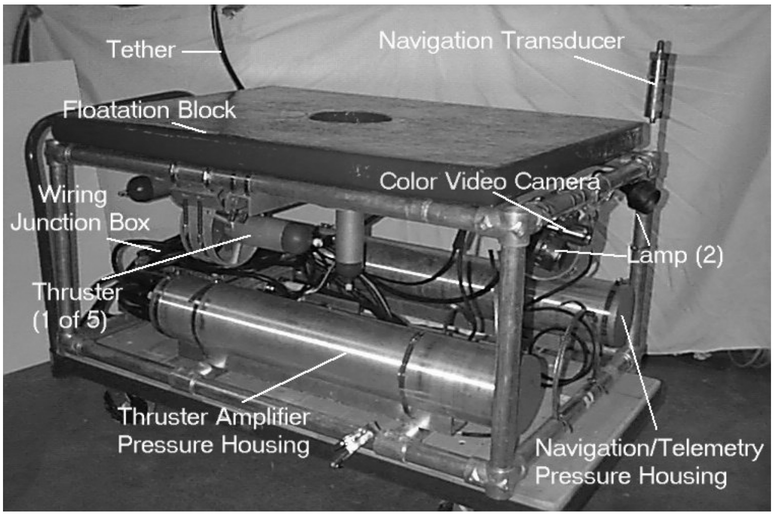

Figure 1: Physical Layout of the JHU ROV

Table 3: Effect of Model Parameter Accuracy

DOF	Controller	Inertia	D_Q	D_L	Buoyancy
x_4	PD (Good)	98.04 [kg m^2]	187.1 [kg m^2]	0 [(kg m^2)/s]	0.1197 [N-m]
x_4	EL (Good)	98.04 [kg m^2]	187.1 [kg m^2]	0 [(kg m^2)/s]	0.1197 [N-m]
x_4	NL (Good)	98.04 [kg m^2]	187.1 [kg m^2]	0 [(kg m^2)/s]	0.1197 [N-m]
x_4	NL (Bad)	200.0 [kg m^2]	100.0 [kg m^2]	0 [(kg m^2)/s]	0 [N-m]

and velocity error norm to quantitatively compare the performance of this family of controllers across a wide range of operating conditions. The position error norm reported for degree of freedom i, was calculated as $X_{err_i} = mean(|x_{d_i} - x_{act_i}|)$ where x_{d_i} and x_{act_i} are the desired/reference and actual logged position of the JHU ROV in degree of freedom i. The velocity error norm was calculated as $V_{err_i} = mean(|v_{d_i} - v_{act_i}|)$, where v_{d_i} and v_{act_i} are the desired/reference and actual logged velocity of the JHU ROV in DOF i.

The experimental position and velocity tracking errors in Figure 3 clearly show that a fixed model based controller isn't necessarily better than a non-model based controller. Clearly, the accuracy of the model parameters themselves play an important role in the performance of the controller. While the "bad" parameter values used were roughly a factor of two different than the "good" values, Table 3, it was enough to degrade the performance significantly. Though the NL controller with "bad" parameters still performed on par with the basic PD controller, it is clear that it wouldn't take a significantly larger error in the parameter values to cause it's performance to drop below the level attained by the basic PD controller.

While the AEL controller's performance was only slightly better then the performance of the NL controller with "bad" parameter values, the ANL controller performed significantly better. This illustrates an advantage of the adaptive model based controllers. If the correct formulation of the control law is chosen, the reliance on accurately identified model parameters disappears.

We conclude that the performance of a fixed model based controller is largely a result of the accuracy of the dynamical plant model used in designing the controller. The results presented in this section clearly indicate that the tracking performance of the fixed model based controllers is dependant on the accuracy of their models. In fact if the model is sufficiently incorrect, a fixed model based controller should not be expected or assumed to perform better than a non-model based controller such as the basic PD controller

Further we conclude that unlike the fixed model based controllers, the adaptive model based controllers are unaffected by the accuracy of the model parameters. Further, if the "right" adaptive control law is implemented, adequate tracking performance can be attained without the accurate identification of dynamical plant model parameters.

4.2 The Effect of Thruster Saturation

The theoretical stability analysis of the model based controllers are based on the assumption that the actuators can deliver whatever force or torque the control law dictates. In the case of the JHU ROV, this means that the thrusters need to be able to provide the required thrust or moment in the respective degree of freedom. What happens when a thruster saturates and thus cannot meet the required level of thrust prescribed by the control law? Analytically, the dynamical plant models presented in Section 2 are no longer valid.

To demonstrate the effects of thruster saturation, a trajectory was chosen for the JHU ROV in the x_3 degree of freedom that would saturate the thrusters in that degree of freedom. This trajectory was run using the PD, EL, NL, AEL, and ANL controllers. The PD feedback and adaptation gains were identical for each controller during these trials.

Comparing the results plotted in Fig 4 it is clear that saturating the thrusters causes severe degradation in the tracking performance of the controllers. The fixed model based controllers appear to handle this unmodelled effect the best while the adaptive model based controllers perform the worst with the thrusters saturating.

We conclude that thruster saturation greatly effects the performance of the model based controllers. While the fixed model base controllers (EL and NL) handled this unmodelled effect

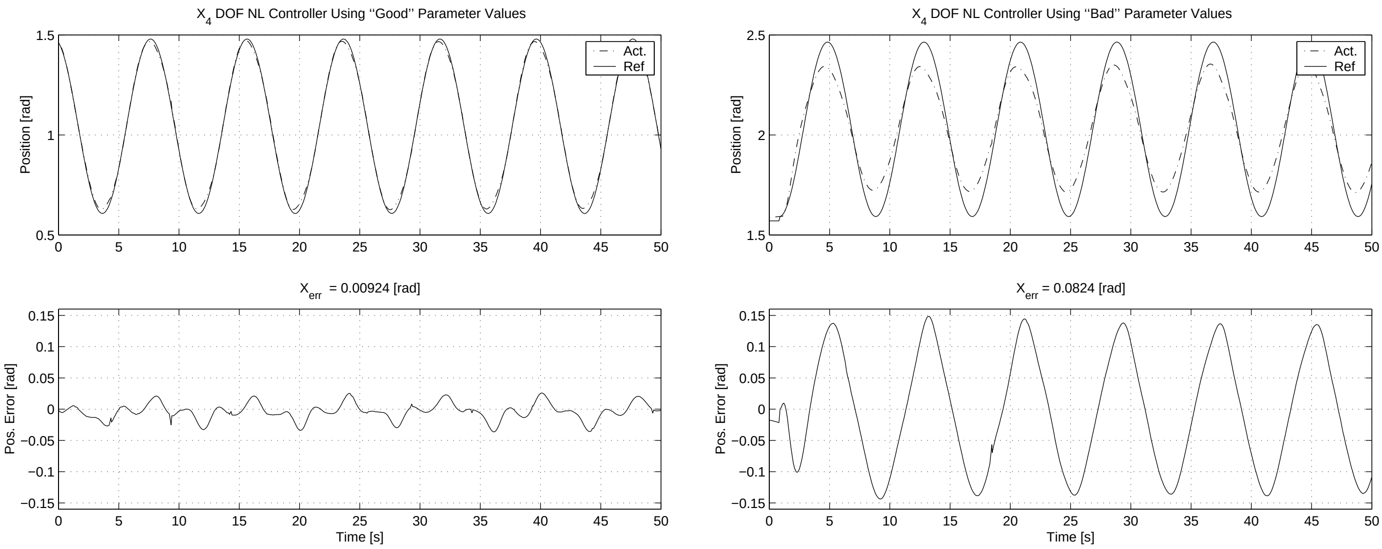

Figure 2: Top: Plot of actual vehicle position (V_{act}) versus desired reference trajectory (V_d) for the NL controller using "good" parameter values (Left) and "bad" parameter values (Right) in the x_4 DOF. Bottom: Plot of position tracking error for the NL controller using "good" parameter values (Left) and "bad" parameter values (Right) in the x_4 DOF. The reference trajectory is a 1/8 Hz sinusoid, $x_d(t) = 0.436cos(2 * pi * 0.785 * t)$[rad]. The PD gains were, $k_p = 250$ and $k_d = 100$, for each controller.

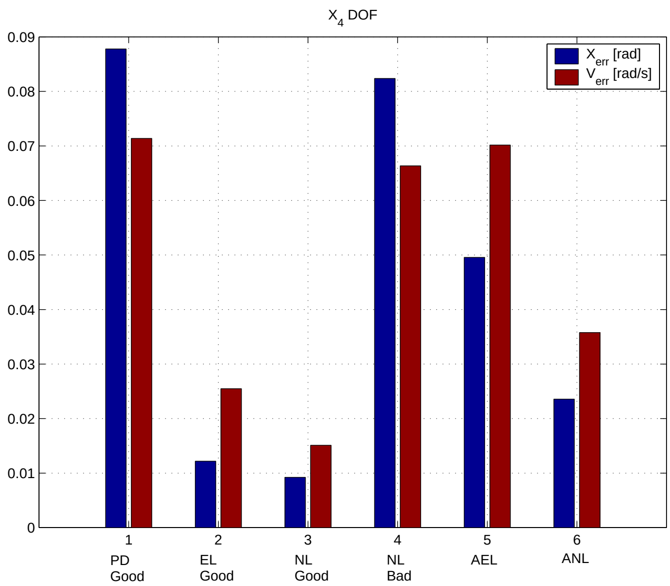

Figure 3: Bar chart of position and velocity tracking error for the PD, EL, NL, AEL, and ANL controllers in the x_4 DOF. The reference trajectory is a 1/8 Hz sinusoid, $x_d(t) = 0.436cos(2 * pi * 0.785 * t)$[rad]. The PD gains were, $k_p = 250$ and $k_d = 100$, for each controller. The adaptation gains were $\gamma_1 = 500$, $\gamma_2 = 50000$, $\gamma_3 = 0$, $\gamma_4 = 1$.

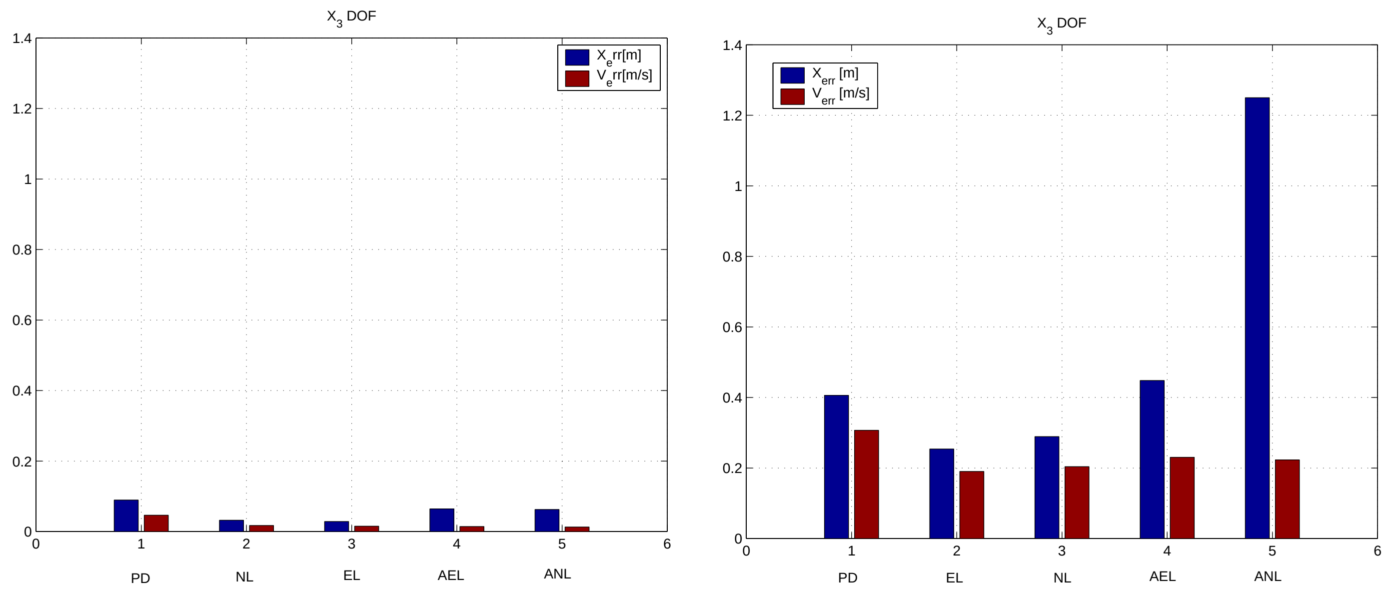

Figure 4: Bar chart of position and velocity tracking error for the PD, EL, NL, AEL, and ANL controllers in the x_3 DOF. The PD gains were, $k_p = 600$ and $k_d = 800$, for each controller. The adaptation gains were $\gamma_1 = 50000$, $\gamma_2 = 5000000$, $\gamma_3 = 0$, $\gamma_4 = 1$. Right: The non-saturating reference trajectory is a 1/12 Hz sinusoid, $x_d(t) = 0.2cos(2 * pi * 0.524 * t)$[m]. Left: The saturating reference trajectory is a 1/8 Hz sinusoid, $x_d(t) = 0.5cos(2 * pi * 0.785 * t)$[m].

the better than the adaptive model based controller (AEL and ANL), all the controllers performed significantly worse with the thrusters saturating.

5 Conclusion

This paper reports an experimental investigation of the robustness of a class of tracking controllers for the low-speed maneuvering of fully actuated underwater vehicles. We have considered the simple but empirically validated case of a decoupled plant dynamical model employing thrust input, constant added mass, constant linear and quadratic drag, and constant buoyancy. We have compared the performance of PD control, two fixed model-based controllers: an exactly linearizing controller (EL), a nonlinear controller (NL) that does not exactly linearize, and the performance of the adaptive extensions of the fixed model based controllers.

Based on the closed-loop experimental performance of this family of controllers we conclude the following points:

1. When fixed model-based controllers employ incorrect plant model parameters, their performance suffers severely. Unlike the their fixed counterparts, the adaptive model-based controllers provide the opportunity for adequate tracking performance without the need for an accurate identification of dynamical plant model parameters.

2. Thruster saturation significantly degrades the performance of the model based controllers. While the fixed model base controllers (EL and NL) handled this unmodelled effect better than the adaptive model based controller (AEL and ANL), the performance of all controllers degrades significantly in the presence of thruster saturation.

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