Robust Adaptive Control of Underwater Vehicles for Precision Operations

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***Abstract*—Using an Autonomous Underwater Vehicle (AUV) for close-proximity operations (e.g., close to the seafloor, a vessel, or divers) requires robust, precise vehicle control. When performing joint human-robot operations, a Robotic Diver Assistant can perform tasks such as tool carrying, worksite illumination, or other tasks that a *dive buddy* might perform. Precise control of the AUV normally requires accurate knowledge of the vehicle's dynamics; however, such models are difficult to obtain. Furthermore, the utility of the resulting model is diminished if, for example, the vehicle configuration changes intentionally or unexpectedly. An ideal control system allows the AUV to handle uncertain environmental conditions, varying payload configurations, and actuator failures. Adaptive control can give an agile AUV the necessary robustness for close-proximity operations, including joint robot-diver operations. Model Reference Adaptive Controls is investigated here for heave control of an agile, tethered, hovering-capable AUV, ACQUAS.**

I. Introduction

Autonomous Underwater Vehicle (AUV) research has mainly focused on open-ocean applications to date, leaving operations close to the seafloor and other objects largely to Remotely Operated Vehicles (ROVs). Yet, Close-Quarters Operations (CQO) are crucial for a variety of scientific and other maritime endeavors. This operational paradigm imposes a novel set of requirements on AUV technologies. In particular, leveraging CQO-capable AUVs to aid divers in the performance of their duties have the potential improved efficiency, effectiveness and safety of dive operations. Diving operations, which occur in a sensory deprived, isolating, dynamic environment, are inherently dangerous. These operations are demanding not only on the divers themselves, but also on the support crew and tends to be resource intensive. A CQO-capable AUV, the Agile Close-Quarters Underwater Autonomous System, or ACQUAS, has been developed by the Naval Postgraduate School's (NPS) Center for Autonomous Vehicle Research (CAVR) to address some of these novel challenges (see Figure 1). In particular, the control of heave channel of this platform, in the presence of mid-mission configuration changes, is the focus of this paper.

The arduous undersea environment subjects the vehicle to many external disturbances such as current and surge. Additionally, actuator failures change the dynamic characteristics of the system. Finally, ACQUAS will be carrying out missions that require varying payloads and system configurations (i.e., delivering or recovering tools). The onboard control system must be capable of handling the resulting changes in vehicle dynamics to ensure precise control. One approach is to attempt to anticipate these changes and develop control laws for each scenario. This practice, known as gain scheduling [1], may be feasible when the changes are predictable and limited in scope, but is normally more appropriate for handling different operating regimes. This is not the case for the application at hand, where the anticipated mid-mission configuration changes are less defined.

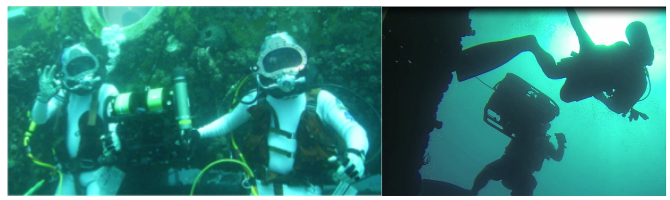

Fig. 1. Close-proximity AUV operations with ACQUAS

This research investigated an alternate control methodology: adaptive control laws can modify the closed-loop system behavior in response to changes in the target system's inherent dynamics, environmental disturbances, and/or platform failures. Unlike traditional control approaches, adaptive control systems are able to operate with a consistent design under a variety of configurations without the need to retune control gains and, unlike gain scheduling, no library of control parameters corresponding to anticipated scenarios is required. Adaptive control is often applied to systems whose process dynamics vary unpredictably or that will be operated in an environment with inconsistent disturbances [1]. Direct Model Reference Adaptive Control (MRAC), which forces the behavior of the closed-loop system to mimic that of a reference model, is investigated here.

The paper is organized as follow: the CQO-capable AUV, ACQUAS, is introduced in Section II. Section III presents a parametric hydro-dynamic model for ACQUAS. Section IV introduces MRAC, before simulation and experimental results are presented in Section V.

A. Related Work

Much research has focused on developing accurate system models for underwater platforms. Such models are used in simulation and controller design. For maritime systems, these models are normally complex since the analysis of rigid body dynamics is insufficient to describe a system that is also subject to hydrodynamic forces. Once augmented for these effects, the resulting model has over 200 unknowns coefficients for a generic 6-degree of freedom model [2]. This generic model can then be specialized for the specific platform through appropriate assumptions. Such specializations for an agile, hover-capable vehicle such as ACQUAS, based on reasonable assumptions about the vehicle shape, composition, symmetry, center and homogeneity of mass, medium density, and vehicle speed, has been presented for example by Fossen [2], Yuh [3], and Weiss and Du Toit [4].

Online model learning, or system identification, forms an integral part to any adaptive control technique [5]. For example, Weiss and Du Toit [4] and Alberti [6] apply recursive learning techniques to experimentally identify of the parametric model coefficients for ACQUAS. These techniques will be leveraged during the adaptive control process in this work.

Adaptive control methods are well established (e.g., [1], [5], [7], [8]) and usually include Model Reference Adaptive Control and Model Identification Adaptive Control, also known as self-tuning control, methods. These methods are further distinguished by the intent of the estimation process: if the control adaptation is estimated directly, then the method is referred to as a direct method. Conversely, if the identified parameter is used in the control law the method is considered to be indirect [5]. These adaptive controllers ideally allow the system to operate successfully with incomplete a priori knowledge of the system model and operating environment.

Adaptive control, specifically MRAC, has been applied to maritime systems (e.g., [9]–[11]). Building on these results, this paper investigates the suitability and limitations of the direct MRAC approach to heave control for ACQUAS, including simulation and experimental results. However, MRAC has known limitations, most notably robustness to unmodeled dynamics and oscillatory behaviors due to high-gain control designs (in an attempt to increase the rate of adaptation). This has inspired in a number of modifications, including the Projection Operator (e.g., [8]).

II. Agile Close-Quarters Underwater Autonomous System, ACQUAS

The Agile Close-Quarters Underwater Autonomous System (ACQUAS) is an augmented SeaBotix vLBV300 (mini-Remotely Operated Vehicle). Refer to Figure 2. The vehicle has 4 degrees of freedom based on the thruster configuration (4 vectored horizontal thrusters and 2 vertical thrusters): surge, sway, heave, and yaw. Limited control in the roll channel is also possible. This tethered platform received commands and power from a surface station.

The vLBV300 has an integrated camera and lighting system on a tilt unit that feeds real-time video to the surface station and is capable of tele-operation only. Several aftermarket sensors and accessories have been added to the system to facilitate autonomous control of the platform: an integrated, fiber-optic gyro based Inertial Navigation system (Greensea Systems) and a Teledyne RDI Explorer Doppler Velocity Log (DVL). The combination of these sensors allow for the tracking of the vehicle's motion without the need for GPS. However, these sensors provide relative measurements only, and is subject to drift and bias, which in turn causes the navigation solution to degrade over time. As a result, the system has been further augmented with an acoustic transducer that allows vehicle tracking via an external beaconing system (including the WHOI Long-Baseline system, or LBL, the Tracklink Ultra-short Baseline system, or USBL, or the Desertstar Short Baseline system, or SBL). These additional aiding sensors are also integrated into the INS solution.

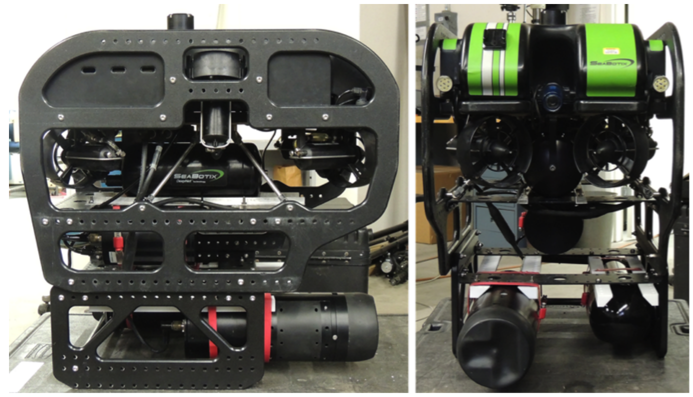

Fig. 2. The Agile Close-Quarters Underwater Autonomous System, ACQUAS

A software architecture has been developed in combination with the INS system that allows autonomous control of the platform. Basic navigation capabilities include station-keeping, waypoint following, and various tele-operation and semi-autonomous modes. These commands are generated on the surface and communicated to the vehicle via the tether.

Finally, the system has been augmented with dual Blueview P900 forward looking sonars (horizontal and vertical heads) and a sideways-mounted MB2250 profiling sonar. This sensor suite allows ACQUAS to perceive the environment for terrain-aided and terrain-relative navigation, obstacle avoidance, and accurate 3D environment mapping: i.e., close-quarters operations.

III. AUV modeling

Kinematic and dynamic equations of motion are required to describe the motion of an AUV in terms of the forces and moments acting on the vehicle [2]. These generic equations were simplified by Weiss [4], [12] in prior work for application to the ACQUAS, resulting in a simplified model (based on relevant assumptions).

A right-handed, body-fixed frame is defined in Figure 3. Rotation about the z-axis is yaw, rotation about the y-axis is pitch, and rotation about the x-axis is roll. The linear and angular velocities are represented by vector $\upsilon = [u, v, w, p, q, r]^T$, where u is the surge, v is the sway, w is the heave velocities (in m/s), respectively. p is the roll, q is the pitch, and r is the

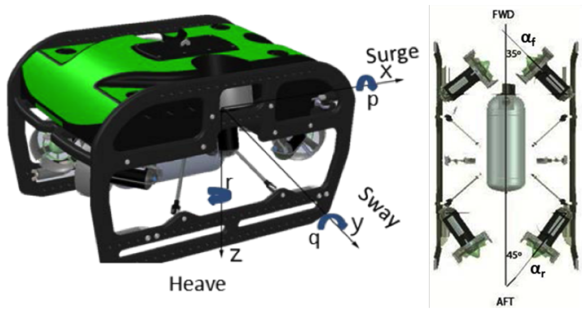

Fig. 3. Body-fixed coordinate frame and thruster configuration for ACQUAS

yaw rates (in rad/s), respectively. The pose of the vehicle in the inertial frame is $\eta = [x, y, z, \phi, \theta, \psi]^T$, where ϕ, θ, and ψ are the Euler angles determined with the *zyx* convention (with rotating frames).

Modeling the non-linear dynamics of the ACQUAS requires the solution of the system [2]:

$$\begin{array}{rcl} \mathbf{M}\dot{\upsilon} + \mathbf{C}(\upsilon)\upsilon + \mathbf{D}(\upsilon)\upsilon + g(\eta) & = & \tau \\ \dot{\eta} & = & \mathbf{J}(\eta)\upsilon \end{array} . \tag{1}$$

The first equation represents the sum of external forces and moments, τ, on the vehicle. $\mathbf{M}$ is the mass term, which contains rigid-body mass (including inertia) and added mass terms due to the hydrodynamic forces and moments on the vehicle: $\mathbf{M} = \mathbf{M}_{RB} + \mathbf{M}_A$. The added mass effects are captured by a 6×6 matrix of coefficients. $\mathbf{C}(\upsilon)$ captures the Coriolis effects, and also include rigid body and added mass terms: $\mathbf{C}(\upsilon) = \mathbf{C}_{RB}(\upsilon) + \mathbf{C}_A(\upsilon)$. Note that these Coriolis terms are defined in terms of the mass properties. $\mathbf{D}(\upsilon)$ is the damping term and typically consists of linear and quadratic components with coupling, and $g(\eta)$ is the hydrodynamic restoring forces. The second equation relates vehicle pose dynamics to body velocities and pose through the 6x6 rotation matrix, $\mathbf{J}(\eta)$, which is defined in terms of the Euler angles [2].

These equations can be simplified by making some basic assumptions about the characteristics of ACQUAS: (i) The x and y position of the center of gravity, center of buoyancy, and the body-frame on the vehicle are coincident, but the z-position may be offset (ii) Three planes of symmetry exist on the vehicle. (iii) All motion occurs at low speed while the vehicle remains fully submerged. (iv) Linear and quadratic damping is present, but coupling in the damping terms are negligible (i.e., lateral motion does not damp longitudinal motion, etc.). (iv) Roll and pitch motions are small. The application of these assumptions yields coupled, but simplified, dynamic equations of motion for the ACQUAS AUV [4]. However, within the scope of this research, only the heave channel motion is considered. This focus permits isolation of the heave direction dynamic equations of motion. Since the heave channel can be excited independently with the vertical thrusters, the other channels and coupling terms can be safely ignored as they are not excited:

$$(m - Z_{\dot{w}})\dot{w} - Z_w w - Z_{w|w|} w\,|w| - (\mathcal{W} - \mathcal{B}) = Z_{prop} \tag{2}$$

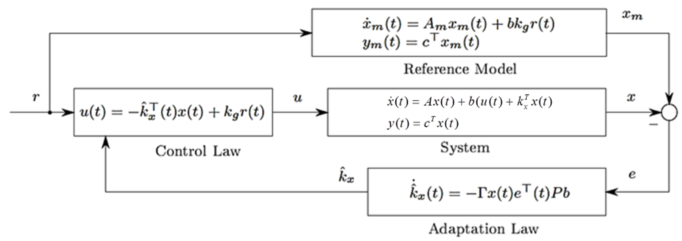

Fig. 4. Direct Model Reference Adaptive Control, after [13]

where Z_{prop} is the heave force generated by the vertical thrusters, m is the mass of the vehicle, $Z_{\dot{w}}$ is the added mass term in the heave direction due to motion in the heave direction, Z_w and $Z_{w|w|}$ are the linear and quadratic damping coefficients, respectively. $\mathcal{W}$ is the weight of the vehicle, and $\mathcal{B}$ is the buoyancy force for the platform. Note: $\mathcal{W} = \mathcal{B}$ for neutrally buoyant systems, but in this case, the mass (and thus weight) of the system is expected to change due to tool delivery or recovery.

IV. Model Reference Adaptive Control

A model reference adaptive control system is composed of four primary parts. The *plant* is the system to be controlled and often contains unknown, unmodeled, or incompletely modeled dynamic parameters; however, the basic structure of the dynamic model is assumed to be known (e.g., from first principles). The *reference system* is a user-defined system which exhibits the desired behavior of the plant. In order to be useful, the reference system's performance must be dynamically achievable by the plant. The *controller* sends a modified command signal to the plant and may contain a number of parameters that are allowed to vary. These parameters are changed in order to achieve asymptotic convergence between the plant and reference model. These control parameters are changed according to an *adaptation law*, which takes as input the error between the model reference and the plant. The general architecture of a direct MRAC system is illustrated in Figure 4.

A. MRAC Algorithm

The implementation of MRAC depends on the parametric model for the system, derived from first principles (refer to Section III). Assume that the plant can be expressed as:

$$\begin{array}{l} \dot{x}(t) = Ax(t) + B\Lambda(u(t) + f(t, x(t))) \\ y(t) = C^T x(t) \end{array} \tag{3}$$

subject to $x(0) = x_0$. $x(t) \in \mathbb{R}^n$ is the system state, $u(t) \in \mathbb{R}^m$ is the control input, and $y(t) \in \mathbb{R}^p$ is the measurement. $A \in \mathbb{R}^{n\times n}$ is the state transition matrix, $B \in \mathbb{R}^{n\times m}$ is the input matrix, and $C \in \mathbb{R}^{n\times p}$ is the output matrix. $\Lambda > 0 \in \mathbb{R}^{m\times m}$ is the diagonal control efficiency matrix (assumed to be unknown). This generic model contains nonlinear terms, $f(t, x(t))$, for which the structure is known from the parametric model. As a consequence, the function, can be written in terms of known basis functions in the regressor, $\Phi(x(t))$, and unknown coefficients, Θ such that $f(t, x(t)) = \Theta^T \Phi(x(t))$. This is known as "matched" uncertainty. Approaches exist to account for unmatched uncertainty as well (e.g., using radical basis functions, etc.) but these extensions are not considered here [8].

Thus, the system dynamics can be written as

$$\begin{aligned} \dot{x}(t) &= Ax(t) + B\Lambda(u(t) + \Theta^T \Phi(x(t))) \\ y(t) &= C^T x(t) \end{aligned} \tag{4}$$

A stable reference system is required. The reference system parameters are selected to represent the ideal (achievable) system behavior in response to bounded command input. The desired response of this model is typically obtained by designing a controller for the baseline system. Assume a reference system of the form:

$$\begin{aligned} \dot{x}_m(t) &= A_m x_m(t) + B_m r(t) \\ y_m(t) &= C_m^T x_m(t) \end{aligned} \tag{5}$$

where is $A_m \in \mathbb{R}^{n \times n}$ Hurwitz, $B_m \in \mathbb{R}^{n \times m}$, and $r(t) \in \mathbb{R}^m$ is the time dependent, bounded reference command input. A_m is chosen to best express the desired system dynamics. $B_m = B\, k_g$, where $k_g = \frac{-1}{C^T A_m^{-1} B}$ [14], to achieve zero steady-state tracking error for a step input. Finally, $C_m = C$.

Once a reference system has been defined, a control law is sought that results in asymptotic tracking of x_m by x. The system must be able to track the reference model even in the presence of the unknown parameters, which may include elements of A, Λ, and Θ. The ideal control solution for achieving this performance, using a feedback + feedforward architecture, is

$$u_{ideal}(t) = K_x^T x(t) + K_r^T r(t) - \Theta^T \Phi(x(t)). \tag{6}$$

This control law is not realizable since it includes unknown parameters. Instead estimates of the quantities are used. The final form of the control signal is then,

$$u(t) = \hat{K}_x^T(t) x(t) + \hat{K}_r^T(t) - \hat{\Theta}^T(t) \Phi(x(t)) \tag{7}$$

and after substituting equation 7 into equation 4, the system dynamics become

$$\begin{aligned} \dot{x}(t) \;\; = \;\; & (A + B\Lambda \hat{K}_x^T(t)) x(t) + \\ & B\Lambda(\hat{K}_r^T(t) r(t) - (\hat{\Theta}(t) - \Theta)^T \Phi(x(t))) \end{aligned} . \tag{8}$$

Equation 8 can be subtracted from equation 5 and combined with the matching conditions, $A + B\Lambda K_x^T(t) = A_m$ and $B\Lambda K_r^T(t) = B\, k_g = B_m$, to produce the closed-loop tracking error dynamics:

$$\begin{aligned} \dot{e}(t) \;\; = \;\; & A_m e(t) + B\Lambda[\Delta K_x(t) x(t) + \\ & \Delta K_r(t) r(t) - \Delta\Theta^T(t) \Phi(x(t))] \end{aligned} \tag{9}$$

where $\Delta K_x(t) = \hat{K}_x(t) - K_x$, $\Delta K_r(t) = \hat{K}_r(t) - K_r$, and $\Delta\Theta(t) = \hat{\Theta}(t) - \Theta$ are the parameter estimation errors [8].

The controller parameters $\hat{K}_x(t)$, $\hat{K}_r(t)$, and $\hat{\Theta}(t)$ are estimated recursively using update laws

$$\begin{aligned} \dot{\hat{K}}_x(t) &= -\,\Gamma_x\, x(t)\, e(t)\, PB\, \mathrm{sgn}(\Lambda) \\ \dot{\hat{K}}_r(t) &= -\,\Gamma_r\, r(t)\, e\,(t) PB\, \mathrm{sgn}(\Lambda) \\ \dot{\hat{\Theta}}(t) &= \Gamma_\Theta\, \Phi(x(t))\, e\,(t) PB\, \mathrm{sgn}(\Lambda) \end{aligned} \tag{10}$$

where $\Gamma_x,\ \Gamma_r,\ \text{and}\, \Gamma_\Theta$ are the adaptation gains that determine the adaptation rates, P is the solution to the Lyapunov equation, ${A_m}^T P + P A_m = -Q$, and $Q \in \mathbb{R}^{n \times n}$ is an arbitrary, positive definite matrix (e.g., identity). Once $\Delta K_x(t) \to 0$, $\Delta K_r(t) \to 0$, and $\Delta\Theta(t) \to 0$, the steady state tracking error tends to zero globally, uniformly, and asymptotically: $\lim_{t \to \infty} ||e(t)|| = 0$ (refer to Theorem 9.2 [8]).

In the presence of unmatched uncertainties, the robustness of a system can be reduced as the controller attempts to converge to a tracking solution. Because the control law cannot adequately compensate for the unmatched dynamics of the system completely, the controller parameters may continue to grow unbounded while the adaptation law seeks a solution, even while the error remains bounded. The Projection Operator modification is introduced to increase controller robustness in this case [8]. The Projection Operator, sometimes called an "anti-windup" modifier, modifies the parameter estimates to enforce uniform boundedness. The resulting adaptation laws are:

$$\begin{aligned} \dot{\hat{K}}_x(t) &= \mathrm{Proj}(\hat{K}_x(t), -\,\Gamma_x\, x(t)\, e(t)\, PB\, \mathrm{sgn}(\Lambda)) \\ \dot{\hat{K}}_r(t) &= \mathrm{Proj}(\hat{K}_r(t), -\,\Gamma_r\, r(t)\, e(t) PB\, \mathrm{sgn}(\Lambda)) \\ \dot{\hat{\Theta}}(t) &= \mathrm{Proj}(\hat{\Theta}(t), \Gamma_\Theta\, \Phi(x(t))\, e(t) PB\, \mathrm{sgn}(\Lambda)) \end{aligned} \tag{11}$$

where

$$\mathrm{Proj}(\hat{\theta}, y) = \begin{cases} y - ||\nabla f(\theta)||^2\, f\,(\theta)\; y & \text{if}\, [f(\theta) > 0 \text{ and} \\ & (y \nabla f(\theta)) > 0] \\ y & \text{otherwise} \end{cases} \tag{12}$$

and

$$\begin{aligned} f(\theta) &= \tfrac{(1+\varepsilon)||\theta||^2 - \theta_{max}^2}{\varepsilon\, \theta_{max}^2} \\ \nabla f(\theta) &= \tfrac{2\,\theta\,(1+\varepsilon)}{\varepsilon\, \theta_{max}^2} \end{aligned} . \tag{13}$$

ε is a projection tolerance and θ_{max} is the parameter bound.

B. MRAC Applied to ACQUAS

Equation 2 can be written in the form of Equation 4 by introducing: $x \equiv w$ and $u \equiv Z_{prop}$, and $y \equiv w$. It follows that $A \equiv \frac{Z_w}{m - Z_{\dot{w}}}$, $B \equiv \frac{1}{m - Z_{\dot{w}}}$, and $C \equiv 1$. The regressor is defined as $\Phi(w) = [\;\; w|w| \quad 1 \;\;]^T$ and $\Theta = [\;\; Z_{w|w|} \quad (\mathcal{W} - \mathcal{B}) \;\;]^T$.

V. Results

The MRAC method was implemented in simulation and on the ACQUAS platform utilizing MathWorks Simulink. From [6], the baseline dynamic model in the heave channel is given by: $m = 35$ kg, $Z_{\dot{w}} = -195.0$ kg, $Z_w = -85.9$ kg/s, and $Z_{w|w|} = 0.0$ kg/m. A 1 kg mass is added to (or removed from) the platform during the experiment. The test objective for the vehicle is to maintain a constant depth (set to 0.1 m).

The MRAC method also requires an ideal, or reference, system that exhibits the desired behavior that is to be tracked. $A_m = -2.0$ was selected in simulation to obtain a relatively aggressive reference system.

Note that the dynamics for the vehicle are defined in terms of the heave velocity: a controller is required to convert the position error to a velocity reference. A simple P-control is used where the velocity reference signal is proportional to the position error: $w_r = P_z(z_r - z)$. z_r and w_r are the position and velocity reference signals, respectively.

A. Simulation Results

To exercise the MRAC implementation in simulation, $P_z = 0.3$ was selected. $\Gamma_x = \Gamma_r = \Gamma_\theta = 2 \times 10^5$ were selected as adaptation gains, resulting in a reasonable balance of controller aggression and response oscillation. For the Projection Operator, $\varepsilon = 0.3$ was selected for the tolerance. For $\hat{K}_x(t)$, the estimate was initialized at $\hat{K}_x(0) = -220$ and a parameter estimate bound of $\theta_{max} = 300$ was used. For $\hat{K}_r(t)$, the estimate was initialized at $\hat{K}_r(0) = 35$ and a parameter estimate bound of $\theta_{max} = 100$ was used. Finally, $\hat{\Theta}(t)$ was initialized at $\hat{\Theta}(0) = \begin{bmatrix} 0 & 0 \end{bmatrix}^T$, with a bound of $\theta_{max} = 200$.

When the 1 kg mass is added to the platform, the vehicle is no longer neutrally buoyant. This affects all the model parameters (through vehicle mass m, see equation 2) but in particular the second element in Θ is affected. The position response of the system is given in Figure **??**. The desired depth stays constant, but the vehicle sinks when the mass is added (recall: z is positive down, according to Figure 3).

From Figure 6, the vehicle heave velocity increases as the vehicle starts to sink, and the control system responds by attempting to decrease this velocity (a negative commanded velocity). The reference model has no knowledge of the change in vehicle dynamics, and simply tracks the reference signal. This response is determined purely by the reference model dynamics. Through the adaptation, the plant attempts to track the reference model to reduce the error, thereby compensating for the changed dynamics. The aggressiveness of this response is determined by the adaptation gains. Setting the gains too high results in oscillatory behavior that reduces the overall controller robustness, while low gains result in slow adaptation to system changes. These effects must be balanced during the design process to obtain an appropriate response.

The unknown parameters in the system are estimated and updated as the system adapts to changes in the dynamics (refer to Figure 7). As expected, the change in mass has a small effect on $\hat{K}_x(t)$ and $\hat{K}_r(t)$. However, the second element of $\hat{\Theta}(t)$ is substantially updated: when 1 kg is added to the vehicle, the controller must cope with an additional 10 N of downwards (positive z) thrust.

The closed-loop system responds to the change in mass within roughly 10 s (see Figure 8). This response can be improved further by using a different (i.e., more aggressive) reference model.

Similar results are obtained when the mass is removed - see Figures 9 and 10.

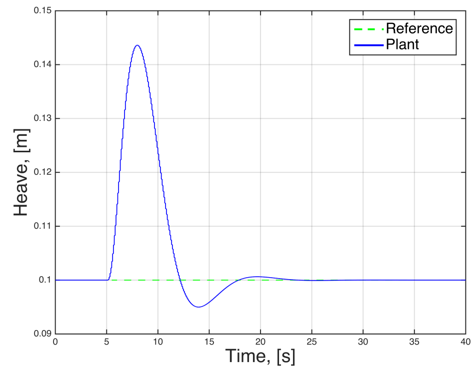

Fig. 5. Position response for 1 kg added to the vehicle (simulation).

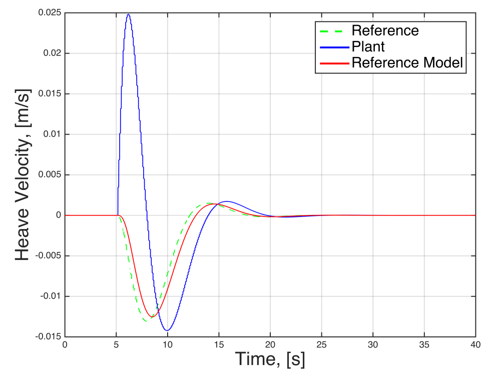

Fig. 6. Velocity response for 1 kg added to the vehicle (simulation).

B. Experimental Results

The MRAC method was additionally implemented on ACQUAS utilizing MathWorks' auto-code generation from Simulink models. Details on the implementation are available at [14]. Similar to the simulation results, a 1 kg mass was added to the vehicle, with the objective of maintaining constant depth. For this experiment, $P_z = 0.2$ and $A_m = -0.4$ to reduce the aggressiveness of the response. The adaptation

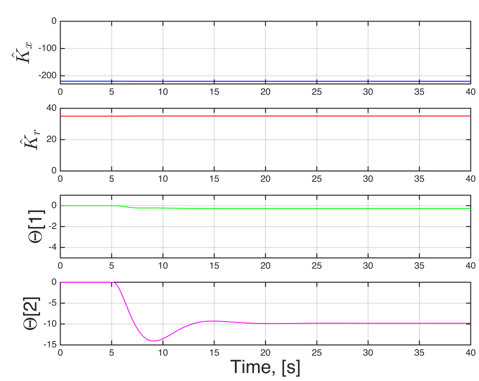

Fig. 7. Estimated parameters for 1 kg added to the vehicle (simulation).

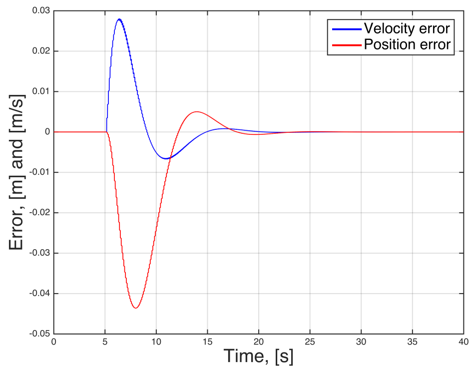

Fig. 8. Errors for 1 kg added to the vehicle (simulation).

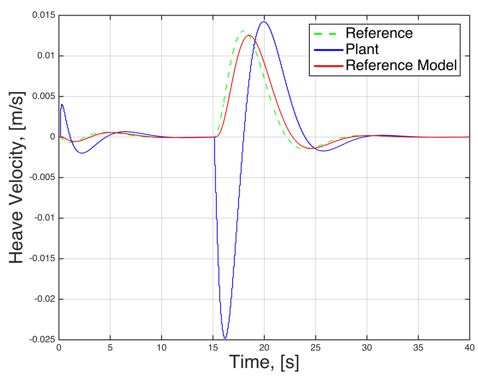

Fig. 9. Velocity response for 1 kg removed from the vehicle (simulation).

gains were also reduced to $\Gamma_x = 6 \times 10^4$, $\Gamma_r = 2 \times 10^4$, and $\Gamma_\theta = 2 \times 10^4$. Furthermore, $\hat{K}_x(0) = -80$, $\hat{K}_r(0) = 140$, and $\hat{\Theta}(0) = [\ 100 \quad 2\ ]^T$. All other parameters remained the same. From Figure 11, it is clear that the velocity response of the system is very similar to the simulation results (refer to Figure 6): the vehicle starts to sink, but as the reference system responds to the change in reference signal, the adaptation process forces the plant to respond as well. Furthermore, the

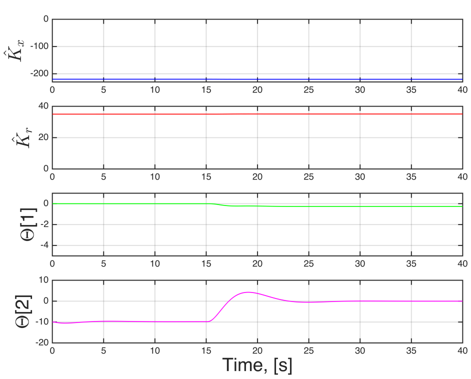

Fig. 10. Estimated parameters for 1 kg removed from the vehicle. (simulation)

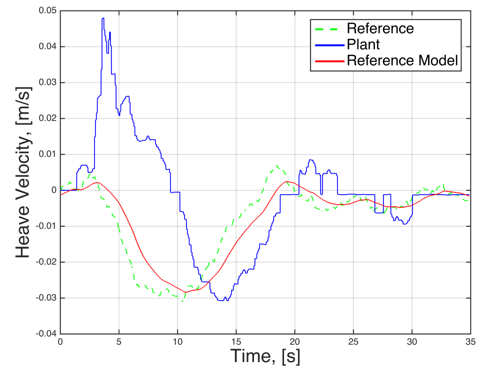

Fig. 11. Measured velocity response for 1 kg added to the vehicle.

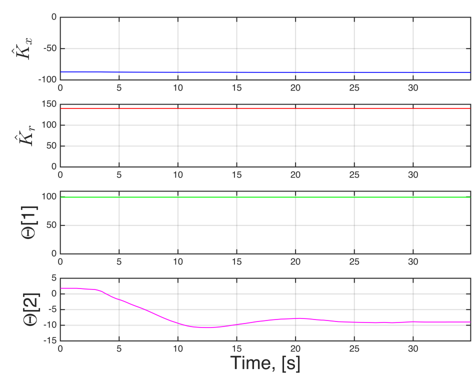

Fig. 12. Online estimated parameters for 1 kg added to the vehicle.

adaptation process correctly modified Θ_2 to account for the 1 kg of additional mass, while the other parameters are largely unaffected (Figure 12).

Similar results are obtained when the additional mass is removed: Figure 13, it is clear that the velocity response of the system is very similar to the simulation results (see Figure 9). Furthermore, the adaptation process correctly modified Θ_2 to account for the 1 kg mass that is removed, while the other parameters are largely unaffected (Figure 14).

C. Limitations of MRAC

While the MRAC system has the potential to effectively control ACQUAS in the presence of uncertain, time-varying parameters and disturbances, its architecture is not without drawbacks. The most prominent limitation is the coupling between robustness and adaptation rate (i.e., the speed with which it can react to changes in the system). Fast adaptation requires high adaptation gains that drive the control system to respond quicker, but with a higher control effort. On the other hand, a robust response requires low gains, allowing the controller to more gradually adapt and arrive at convergence without overshoot and with minimal control effort. Because these two mechanisms are opposing, they must be balanced at the cost of performance. In fact, MRAC does not provide any

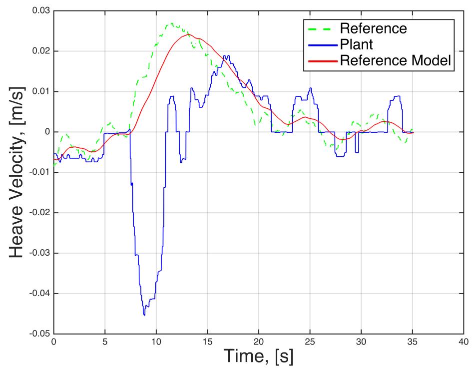

Fig. 13. Measured velocity response for 1 kg removed from the vehicle.

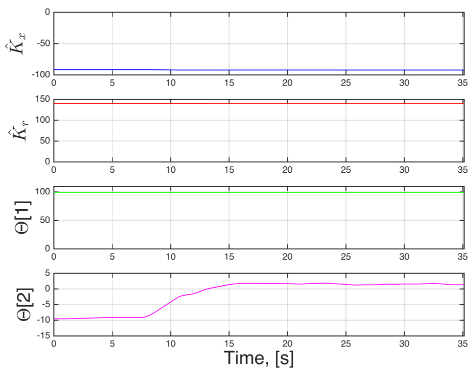

Fig. 14. Online estimated parameters for 1 kg removed from the vehicle.

guarantees on the transient response of the systeml [13]. If a system is tuned to favor robustness, speed will be sacrificed.

Control gains are often selected through empirical evaluation. The stability of the MRAC system response is normally related to the parameter estimation process. Parameter estimate drift can cause the estimates to become unbounded. The addition of modifiers to the adaptation law (e.g., Projection Operator), alleviates some of the robustness concerns. However, these modifications of the adaptation process prevents the system from reacting optimally at the cost of a temporary deviation from the optimal reduction in output error.

As a potential remedy to these limitations, $\mathcal{L}1$ adaptive control [13] will be evaluated in follow-on work. This alternative decouples the adaptation properties of the controller from the stability of the controller, allowing for fast adaptation and robust stability. Furthermore, the approach establishes some guarantees on the transient response of the system.

VI. Conclusion

The application of AUVs in close proximity to other objects require precise control of these platforms in the presence of environmental disturbances. However, precision controller design requires accurate dynamic models. Such models are extremely hard to obtain for underwater platforms. On the other hand, the application of ACQUAS require handling vehicle configuration changes during mission execution. The application of Model Reference Adaptive Control to the heave control of ACQUAS was investigated. The control approach was first implemented in simulation to model a 1 kg mass change during mission execution. The controller parameters (notably adaptation gains) were tuned to obtain a reasonable dynamic response. The appropriateness of the parameter estimation process was also verified in the context of the configuration change. Next, the approach was implemented and tested in experimentation on ACQUAS. Although the MRAC controller responded well to the change, limitations with the approach exist. Notably, the coupling between adaptation rate and robustness limits the speed of response obtainable. Furthermore, the approach does not provide guarantees for the transient response of the system. The authors recommend the investigation of $\mathcal{L}1$ adaptive control to overcome these limitations.

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