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References


Modeling and Control of Underwater Robotic Vehicles

J. YUH

Abstract—Remotely operated, underwater robotic vehicles have become the important tool to explore the secret life undersea. They are used for various purposes: inspection, recovery, construction, etc. With the increased utilization of remotely operated vehicles in subsea applications, the development of autonomous vehicles becomes highly desirable to enhance operator efficiency. However, engineering problems associated with the high density, nonuniform and unstructured seawater environment, and the nonlinear response of the vehicle make a high degree of autonomy difficult to achieve. The dynamic model of the untethered vehicle is presented, and an adaptive control strategy for such vehicles is described. The robustness of the control system with respect to the nonlinear dynamic behavior and parameter uncertainties is investigated by computer simulation. The results show that the use of the adaptive control system can provide the high performance of the vehicle in the presence of unpredictable changes in the dynamics of the vehicle and its environment.

I. INTRODUCTION

A large portion of the earth is covered by seawater and has not been fully explored, so plenty of resources still remain in a natural condition. In a recent report [1] the National Science Foundation, seven critical areas in ocean system engineering were identified as follows: system for characterization of the sea bottom resources; systems for characterization of the water column resources; waste management systems; transport, power and communication systems; reliability of ocean systems; materials in the ocean environment; analysis and application of ocean data to develop ocean resources. It was also concluded in the report that the area of underwater robotics should be supported in all of the above areas. It is obvious that all kinds of ocean activities, including both scientific ocean related research and commercial utilization of ocean resources, will be greatly enhanced by the development of an intelligent, robotic underwater work system.

Current underwater working methods include scuba, remotely operated vehicle (ROV), submarine, etc. During the last few years, the use of ROVs has rapidly increased since such a vehicle can be operated in the deeper and riskier areas where divers cannot reach. In the undersea environment, ROVs are used for various work assignments. Among them are: pipelining, inspection, data collection, construction, maintenance and re-

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The author is with the Department of Mechanical Engineering, University of Hawaii, Honolulu, Hawaii 96822.

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pairing underwater equipment, etc. However, subsystems in the current vehicles are immature compared to those in on-land systems and therefore, performance of the vehicle is limited. High technologies developed for on-land systems cannot be directly adapted to underwater vehicle systems since such vehicles have different dynamic characteristics from on-land vehicles, and their operating environment is unstructured. Effect of high density water motion on the vehicle is also significant.

The dynamics of ROVs are fundamentally nonlinear in nature due to rigid body coupling and the hydrodynamic forces on the vehicle. This nonlinear dynamic behavior of ROVs is similar to the well-known rigid body vehicle motion of aircraft and conventional submarines although there are a couple of important differences: 1) ROVs usually have comparable velocities along all three axes. Therefore, control techniques that depend on linearization of the equations of motion about a single forward operating speed cannot be used as effectively as they can with aircraft and submarines. 2) The high density of water sets ROVs and submarines apart from aircraft because the forces and moments produced by fluid motion are significant and they cannot be conventionally combined with the forces and moments produced by vehicle motion to form functions of relative motion only (except for the special case of a neutrally buoyant vehicle). In addition, the added mass aspect of the density of the medium must be considered and results in control response characteristics that are long in comparison with human anticipation and analysis capabilities. Therefore, satisfactory performance of the vehicle cannot be obtained without consideration of the nonlinear equations of motion in designing the vehicle control system. Furthermore, the hydrodynamic coefficients are often poorly known and a variety of unmeasurable disturbances are present due to multidirectional currents. Also, considering that the vehicle dynamics can change appreciably as different sensors and work packages are used, it is vehicle control system interms of speed and accuracy. Consequently, an intelligent system guidance and control strategy must be developed.

The dynamic equations of motion for marine vehicles have been shown in the literature [2], [3]. These models, which were developed primarily for ships and submarines, use coordinate systems which simplify the mathematics involved but limit their applicability to more ROVs. During the last few years, several control strategies for ROVs have been discussed. Kazerooni and Sheridan [4] have developed the control system based on the Clayton–Bishop model by using the pole placement and observer method. Their system can be used when all states of the system are not available. However, robustness of the control system with respect to parameter uncertainties cannot be guaranteed. Yorger and Slotine [5] have proposed a series of single-input and single-output continuous-time controllers by using the sliding control technique. Robustness of their control system with respect to parameter uncertainties was demonstrated by computer simulation using a planar model of the University of New Hampshire experimental autonomous vehicle (EAVE). In their simulation, the effect of pitch, roll and vertical movement were not considered, inertia terms were simplified by placing the moving coordinate system at the center of mass, and the effect of a single thruster on more than one velocity was ignored. Goheen et al. [6] have suggested the use of a self-testing controller that requires the manual piloting of the vehicle to select the closed-loop poles before operations begin and after any equipment changes are made. Goheen et al. [7] have proposed an adaptive autopilot for ROVs. The control system used in their simulation is poorly described with several errors in their paper. Without showing the result, they claim that their control system can cope with sudden or slowly varying changes in vehicle dynamics better that the fixed-gain controller. However, large tracking errors, using their control system, are still observed from the result of their simulation. Therefore, the evaluation of their control algorithm cannot be completed.

To increase the autonomy, various subsystems of the vehicle have been studied. In this paper, we present the result of the recent development on the control system of the vehicle. This paper is organized as follows. In Section II, since dynamic analysis of such vehicles is a cornerstone to developing advanced technology vehicles that include intelligent system guidance and control architectures, we derive the equations of motion of the vehicle, considering the effect of hydrodynamics. Section III proposes an adaptive control strategy to control the vehicle. In the literature, the advantages of the use of adaptive control techniques have been described for various nonlinear dynamic systems such as industrial robots [8] and large tankers [9]. When parameters of the system to be controlled are poorly known, the use of an adaptive control strategy is encouraged. Since the dynamic behavior of ROVs is nonlinear and hydrodynamic coefficients are poorly known, adaptive control techniques are very attractive in this application. The robustness of the control system under varying degrees of parameter uncertainty is investigated for the case of planar motion, and results of case study are discussed in Section IV before the conclusion.

II. DYNAMIC MODEL

In this section, the ROV dynamic model is presented. We assume that the vehicle is powered by onboard battery stacks, and communicates with the surface mothership or ground station by unthethered communication links such as ultrasonic waves. Therefore, the effects of tether are not considered in the dynamic model. In this paper, the lengthy, detailed derivation procedure of the dynamic model is not included. A detailed derivation of this model is shown in [10].

A. Coordinate Systems

The dynamic model uses two orthogonal coordinate systems: global coordinate system, \((O,\hat{I},\hat{J},\hat{K})\), which remains fixed at the ocean surface (mother ship) with origin \(O\), pointing down into the water normal to the surface and \(\hat{I}\) and \(\hat{J}\) chosen in any two convenient mutually perpendicular horizontal directions with the only restriction being that the axes form a right-handed system; and a local coordinate system, \((P,i,j,k)\), which is fixed on the vehicle with origin at \(P\), pointing through the nose of the vehicle, \(k\) pointing through the belly of the vehicle and \(j\) completing the right-handed system. The position and orientation of the vehicle in global coordinates can be specified by \(\vec{R}_p\), the vector from \(O\) to \(P\), and the Euler angles \(\phi, \theta, \phi\). Transformation of forces and motions from local to global coordinates can be accomplished by using the transformation matrices \([T]\) and \([T']\) and from global to local by using its inverse (which is just \([T']\)^{-1} since \([T]\) is an orthogonal matrix) where

\[
[T] = \begin{bmatrix}
\cos \phi & \cos \theta & \cos \phi \sin \theta + \sin \phi \\
\sin \phi & \sin \theta & -\cos \phi \sin \theta + \cos \phi \\
-\sin \phi & \cos \theta & \cos \phi \sin \theta - \sin \phi 
\end{bmatrix}.
\]

The development of the dynamic model is carried out in the local coordinate system since the motion of the vehicle is usually described in reference to this system.
B. Rigid Body Six-Degree-of-Freedom Dynamics

In developing the rigid body equations of motion, two assumptions are made: the mass of the vehicle remains constant in time and the effect of earth rotation can be neglected. It is customary to choose the center of mass of a rigid body as the origin of the local coordinate system to simplify the analysis involved. However, for underwater vehicles, it is more convenient to develop the equations for an arbitrary origin to provide flexibility in choosing an origin which takes advantage of the geometrical properties of the vehicle to facilitate the expression of the complex hydrostatic and hydrodynamic force acting upon it. The equations of motion for a rigid body of mass \( m \) with an arbitrary origin are summarized below.

Translational Motion: \( F = m \left[ \dot{U} + \Omega \times R_c + \Omega \times (\Omega \times R_c) \right] \) \tag{2}

Rotational Motion: \( G = \frac{d}{dt} \left( \left[ I \right] \Omega \right) + m (R_c \times \dot{U}) \) \tag{3}

where \( F = [X, Y, Z]^T \) the resultant external force, \( G = [K, M, N]^T \) the resultant external moment, \( U = [u, v, w]^T \) the velocity of the origin, \( \Omega = [p, q, r]^T \) the angular velocity about the origin, \( R_c = [x_c, y_c, z_c]^T \), the position of the center of mass in local coordinates, and

\[
[I] = \begin{bmatrix}
1 & -1 & -1 \\
-1 & 1 & -1 \\
-1 & -1 & 1 \\
\end{bmatrix}
\]

the inertia tensor with respect to the origin.

It is important to recognize that in the expressions above, the derivative of a vector will in general not be equal to the vector, and the derivative of the components of the unit vectors \( \hat{i}, \hat{j}, \hat{k} \) change direction as the vehicle rotates producing centrifugal acceleration terms. Therefore, in evaluating the vector derivatives, the following expressions must be used:

\[
\frac{d}{dt} \hat{i} = q \hat{j} - p \hat{k}, \quad \frac{d}{dt} \hat{j} = -p \hat{i} + r \hat{k}, \quad \frac{d}{dt} \hat{k} = q \hat{i} - r \hat{j} \tag{4}
\]

C. Hydrodynamic Forces and Moments

The hydrodynamic forces and moments acting on an ROV are described below assuming that fluid rotation is negligible and there is a current with a velocity \( U_c \). If \( U_j \) is expressed in terms of the local coordinate system, the velocity of the vehicle relative to the fluid is

\[
U_r = U - [T]^T U_j \tag{5}
\]

Added Mass: Since the density of water is similar to the density of an ROV, additional inertia terms must be introduced to account for the effective mass of surrounding fluid that must be accelerated with the vehicle. These added mass coefficients are defined as the proportionality constants which relate each of the linear and angular accelerations with each of the hydrodynamic forces and moments they generate. For example, the hydrodynamic force along the \( x \)-axis due to acceleration in the \( x \)-direction is expressed as

\[
X_{h,x} = - X_{h,\ddot{x}} \text{ where } X_{h,\ddot{x}} = \ddot{X} / \ddot{\dot{x}} \tag{6}
\]

In a similar manner, all other added mass coefficients can be defined and assembled into an added mass matrix \( [A] \). Considering the effect of the current and centripetal acceleration components \( (4) \), the force and moment due to added mass can be obtained from

\[
\begin{bmatrix}
F \\
G \\
\end{bmatrix}_{\text{A}} = \frac{d}{dt} \left( [A] \begin{bmatrix}
U_c \\
\dot{U}_j \\
\end{bmatrix} \right) \tag{7}
\]

Fluid Motion: For a vehicle moving in a low density fluid, such as an airplane, the forces and moments exerted on the vehicle by fluid motion can be neglected. However, for an ROV traveling at low speeds in the ocean, these effects are significant and must be included in the dynamic model:

\[
F_r = m_l U_j, \quad \text{and} \quad G_r = m_l (R_{b} \times \dot{U}_j) \tag{8}
\]

where \( m_l \) is the mass of the vehicle displaced by the vehicle and \( R_b = [x_b, y_b, z_b]^T \) is the position of the center of buoyancy in local coordinates. It should be noted that except for the special case of a neutrally buoyant vehicle, the mass of the fluid displaced by the vehicle will not be equal to the mass of the vehicle. Therefore, the forces and moments produced by vehicle motion and fluid motion cannot be conveniently combined into functions of relative motion only. However, in \( (7) \), relative velocity can be used because the \textit{added mass coefficients} are dependent only on the body geometry and not on \( m_l \).

The Drag: The drag is usually described as a force proportional to the square of the corresponding relative motion of the vehicle. For example, the drag force along the \( x \)-axis due to relative velocity in the \( x \)-direction is expressed as \( -X_m \left| u \right| u \), where \( X_m = \ddot{X} / \ddot{u} \), and the drag moment along the \( z \)-axis due to the angular velocity \( r \) is expressed as \( -N_y r / r \), where \( N_y = \ddot{N} / \ddot{r} \). The drag force and moment are then denoted by \( F_{D,x} \) and \( G_{D,z} \), respectively.

D. Weight and Buoyancy

The gravitational force and buoyant force are defined in terms of the global coordinate system so they must be transformed to the local coordinate systems:

\[
F_w = m g [\begin{bmatrix} -\sin \theta & \cos \theta & 0 \end{bmatrix} \sin \phi \cos \phi]^T, \quad \text{and} \quad F_B = -\rho g V [\begin{bmatrix} -\sin \theta & \cos \theta & 0 \end{bmatrix} \sin \phi \cos \phi]^T \tag{9}
\]

where \( g \) is the gravitational acceleration, \( \rho \) is the fluid density and \( V \) is the volume of the fluid displaced by the vehicle. The moments generated by these forces can be expressed in terms of the positions of the center of mass \( C \), and the center of buoyancy \( B \):

\[
G_w = R_c \times F_w, \quad \text{and} \quad G_B = R_B \times F_B \tag{10}
\]

where \( R_c \) and \( R_B \) are the respective positions of the center of mass and the center of buoyancy in the local coordinate system.

E. Thrusters

The resultant force and moment of a thruster configuration consisting of \( N \) thrusters can be expressed as the vector sum of the force and moment from each individual thruster:

\[
F_T = \sum_{i=1}^{N} F_{T_i}, \quad \text{and} \quad G_T = \sum_{i=1}^{N} G_{T_i} + \sum_{i=1}^{N} R_{T_i} \times F_{T_i} \tag{11}
\]

where \( R_{T_i} \) is the position of the \( i \)-th thruster in local coordinates. The magnitudes of the thruster and torque generated by the \( i \)-th thruster can be expressed as

\[
|F_{T_i}| = K_{T_i} n_i^2 D_i^4, \quad \text{and} \quad |G_{T_i}| = K_{D_i} n_i^2 D_i^5 \tag{12}
\]

where \( D_i \) is the diameter of the thruster, \( n_i \) is the angular speed of the thruster shaft and \( K_{T_i} \) and \( K_{D_i} \) are the thruster and torque coefficients of the thruster \([11]\). The major problem that is encountered in thruster modeling is that they behave as highly nonlinear actuators. Therefore, the thruster and torque coefficients cannot be represented as being constant but rather must be expressed as functions of the advanced coefficient

\[
J = V / nD \tag{13}
\]

where \( V \) is the axial speed of the thruster.
F. ROV Dynamic Model

All external forces and moments can now be consolidated into the rigid body equations of motion (2) and (3), to produce the ROV dynamic model. However, to provide a form that will be suitable for control purposes, some rearrangement of terms is required. First, all added mass terms obtained from (7) which have fluid velocity and acceleration components \((u, v, w, p, q, r)\) are combined with the fluid motion forces and moments (8) into a fluid vector denoted by the subscript \(F\). Next, the mass matrix \([M]\) consisting of all the coefficients of inertia and added mass terms with vehicle acceleration components \((u, v, w, p, q, r)\) is defined as

\[
[M] = \begin{bmatrix}
  m + X_p & X_r & X_q \\
  Y_p & m + Y_r & Y_q \\
  Z_p & Z_r & m + Z_q \\
  K_p & -m_r + K_r & m_r + K_q \\
  m_z + M_p & M_r & -m_x + M_q \\
  -m_y + N_p & m_x + N_q & N_r
\end{bmatrix}
\]

Finally, all remaining added mass terms are combined with the remaining inertial terms into a dynamics vector denoted by the subscript \(D\) to produce the final form of the model:

\[
[M]Q = \begin{bmatrix}
  F \\
  G_F \\
  G_F \\
  G_F \\
  G_F \\
  G_F
\end{bmatrix} + \begin{bmatrix}
  F \\
  G_F \\
  G_F \\
  G_F \\
  G_F \\
  G_F
\end{bmatrix} + \begin{bmatrix}
  F \\
  G_F \\
  G_F \\
  G_F \\
  G_F \\
  G_F
\end{bmatrix} + \begin{bmatrix}
  F \\
  G_F \\
  G_F \\
  G_F \\
  G_F \\
  G_F
\end{bmatrix} + \begin{bmatrix}
  F \\
  G_F \\
  G_F \\
  G_F \\
  G_F \\
  G_F
\end{bmatrix}
\]

where \(Q = [\dot{u}, \dot{v}, \dot{w}, \dot{p}, \dot{q}, \dot{r}]^T\).

III. CONTROL SYSTEM

The control system is determined using a discrete-time approximation of the ROV dynamic model (15) that can be expressed by the following vector equation:

\[
V(k+1) = A1 \cdot V(k) + A0 + B1 \cdot U(k)
\]

where \(k\) is the \(k\)th sampling time step, \(V\) is the six-dimensional (6-D) velocity vector of the ROV and \(U\) is the 6-D vector of forces and moments generated by the thrusters. If the parameters in the discrete-time model were known exactly, a conventional digital control law could be determined using classical methods. However, since the poorly known hydrodynamic coefficients are included among the parameters of the dynamic model, a conventional control scheme cannot guarantee high performance in ROV motion control. Therefore, a parameter adaptation algorithm (PAA) is introduced to solve this problem. The PAA estimates the parameters in the discrete-time model at each sampling time step using input-output measurements from the ROV. These estimates are then used to adjust the controller gains to provide the required control signals. In this section, a discrete-time adaptive velocity controller for ROVs is designed using the self-tuning control principle.

The basis of this control algorithm is a linear predictor that is designed with the aim that the prediction error vanishes according to

\[
\lim_{k \to \infty} E(k+1) = C_p(q^{-1})[V(k+1) - \hat{V}(k+1)] = 0
\]

with the following PAA:

\[
\hat{V}(k+1) = \hat{V}(k) + F(k+1)\Phi(k+1)^T
\]

\[
F(k+1) = \frac{1}{X_p \lambda(k)} \begin{bmatrix}
 F(k) - \frac{F(k) \Phi(k) \Phi^T(k) F(k)}{\lambda(k)} + \Phi(k)^T F(k) \Phi(k)
\end{bmatrix}
\]

\[
0 < \lambda(k) < 1, 0 < \lambda_1 < 2, F(0) > 0
\]

\[
\hat{V}(k+1) = \hat{V}(k) + F(k+1)\Phi(k+1)^T
\]

where \(\lambda(k)\) is used to denote an estimated value,

\[
\hat{F}(k) = \begin{bmatrix}
 X_p & m_z + X_p & -m_z + X_p \\
 m_r + Z_p & -m_r + Z_p & Z_r \\
 -m_c + K_p & I_c + K_p & -I_c + K_c \\
 -m_x + M_p & I_x + M_p & -I_x + M_x \\
 -m_y + N_p & I_y + N_p & I_z + N_z
\end{bmatrix}
\]

and

\[
\Phi^T(k) = \begin{bmatrix}
 X_p & m_z + X_p & -m_z + X_p \\
 m_r + Z_p & -m_r + Z_p & Z_r \\
 -m_c + K_p & I_c + K_p & -I_c + K_c \\
 -m_x + M_p & I_x + M_p & -I_x + M_x \\
 -m_y + N_p & I_y + N_p & I_z + N_z
\end{bmatrix}
\]

where \(\lambda(k)\) and \(\lambda_1(k)\) are included among the parameters of the dynamic model, \(\lambda(0)\) and \(\lambda_1(0)\) are initialized with values of 1.0. The parameter values estimated by the predictor are then used at each time step to compute a control signal such that the output of the predictor follows the desired trajectory.

\[
C_p(q^{-1})V(k+1) = C_p(q^{-1})V_d(k+1)
\]

Substituting (18) into (23) and solving for \(U(k)\),

\[
U(k) = \hat{B}(k)^{-1}[C_p(q^{-1})V_d(k+1) - \hat{R}(k)V(k) - \hat{W}(k)d]
\]

which is the desired control law.

To summarize, in the proposed control algorithm the parameters of the predictor are estimated at each time step using (12) and (20) then the values of these estimated parameters are used to compute the control signal in (24). The control scheme presented here is extremely simple and therefore the computational time required to calculate the adaptive control signal (24) is very short. As a result, the proposed control algorithm could be implemented using a high sampling rate such as 1 KHz. Also, this control approach was well implemented for industrial robot
systems which usually have the faster motion and the shorter operating time period for one task than the underwater vehicle. The diagram of this control system is shown in Fig. 1. In the next section, a case study is presented to show the use of the proposed control scheme for an ROV.

IV. CASE STUDY

To investigate the robustness of the control system, a computer simulation was performed for the plane motion of a ROV modeled after the Dolphin 3K presented in [13]. For this ROV, motions in the horizontal plane may be described by the following set of equations:

\[
\begin{align*}
(m + X_u) \ddot{u} - my_1 \dot{r} &= mx_1 \dot{r}^2 + (m + Y_r) \dot{r} \\
-X_{u1} u \dot{u} &= (m + Y_r) t + X_T \\
(m + Y_r) i + mx_1 \dot{r} &= my_1 \dot{r}^2 + (m + x_1) ur \\
-Y_r i \dot{r} + (m + X_r) \dot{u} r &= Y_T \\
-my_1 \ddot{r} + (I_z + N_r) \dot{r} &= -mr(x, u + y, e) - N_r i \dot{r} + m_r(x, y, u + y, e) + N_T.
\end{align*}
\]

(25)

Numerical values of the parameters in (25) are assumed from [13] as follows: \(m = 3500 \text{ kg}, m_r = 3506 \text{ kg}, x_1 = -0.1 \text{ m}, y_1 = 0, x_2 = -0.1 \text{ m}, y_2 = 0 \text{ and } I_z = 3827 \text{ kg-m}^2\). One possible choice of the parameter matrices for (16), using the dynamic model (15), is \(A1 = I, B1 = \Delta M^{-1} \text{ and } A0 = \Delta M^{-1} F_i \) where \(\Delta t\) is the sampling time interval, \(M\) is the mass matrix and \(F_i\) represents the nonlinear terms and all the external forces and moments other than those due to the thrusters. Based on this choice, the adaptive control system is determined for the case study.

In the simulation, the following considerations are made:

1) The desired velocities \(u^d, \dot{e}^d\) and \(r^d\) are generated by using the trapezoidal speed law shown in Fig. 2.
2) The regulation dynamic of the parameter estimates for the controller in (24) are arbitrarily chosen as:

\[
B1(0) = \begin{bmatrix}
1e^{-5} & 0 & 0 \\
0 & 1e^{-5} & 1e^{-6} \\
0 & 1e^{-6} & 1e^{-5}
\end{bmatrix}
\]

and

\[A0(0) = 0.\]

4) A constant current of velocity \(u_f\) is assumed in the \(X\)-direction of the global coordinate system. 5) Since \(A1\) is chosen as the identity matrix, the PAA is designed to estimate the parameter matrices \(B1\) and \(A0\). 6) The initial values of the adaptation gain matrix is selected as \(F(0) = I, F(k)\) is updated using the constant trace algorithm with \(A_1(k) = A_1(k)\) and \(A_0(k)\) is computed such that \(\text{trace}(F(k)) = \text{trace}(F(0))\). 7) The velocities of the system are measured by numerically integrating the nonlinear differential equations (25). 8) A sampling time step of \(\Delta t = 0.05 \text{ s}\) is used. 9) Robustness of the algorithm with respect to hydrodynamic coefficients and current is tested by implementing the control system for the following sets of constant system parameters and current velocities:

Case 1: \(X_u = 693 \text{ kg}, Y_r = 762 \text{ kg}, N_r = 3817 \text{ kg-m}^2\), \(X_{u1} = 1646 \text{ kg/m}, Y_r = 2273 \text{ kg-m/s}, N_{u1} = 5457 \text{ kg/m}^2, u_f = 0\).

Case 2: All hydrodynamic coefficients increased by 100% from case 1 and \(u_f = 0.5 \text{ m/s}\).

Case 3: All hydrodynamic coefficients increased by 100% from case 1 and \(u_f = -0.5 \text{ m/s}\).

Note that numerical values used for Case 1 are also assumed from [13].

The results of the computer simulations are shown in Figs. 3 through 15 for each case using the control law with PAA and the control law without PAA. Figs. 3 through 11 show the velocity tracking errors which are defined as follows: Surging rate error, \(E(1) = u^d - u, \) Swaying rate error, \(E(2) = e^d - e, \) and Heading rate error, \(E(3) = r^d - r\). Fig. 11 shows the heading angle and Figs. 13–15 show the thrust and torque required to sustain the desired velocities.

The vehicle was originally heading in the \(X\)-direction of the global coordinate. From the desired heading angular velocity profile (Fig. 2), the desired heading angular displacement is 3 rad, and therefore the vehicle almost heads in negative \(X\)-direction at steady state. The result of the simulation for each case.
also heading in X-direction at the beginning, the vehicle velocity in X-direction is far below the desired velocity in that direction without PAA and Fig. 9 shows large surging rate errors especially around 10 sec. With PAA, the surging rate errors are very small except during the first 10 sec. which is the adaptation period.

Figs. 4, 7 and 10 show the swaying rate error for cases 1, 2 and 3, respectively. The effect of current velocity on the vehicle velocity in y-direction of the local coordinates is small at steady state. Each case shows small swaying rate error at steady state. However, during the operating time period, each case shows large swaying rate error without PAA while each case shows very small swaying rate errors with PAA. Figs. 5, 8, and 11 show the heading rate error for cases 1, 2 and 3, respectively. One can have the same conclusion as one for the swaying rate error.

Fig. 12 shows the heading angle of the vehicle for each case. With PAA, Fig. 11 shows the same result of no steady error and desired heading angle for these three cases. Without the PAA, results show the steady error for each case.

Figs. 13–15 show the forward thrust, lateral thrust and thrust torque, respectively. In this study, the power limitation of the vehicle thrusters were not considered. One can observe the large variation in the control efforts with PAA during the initial adaptation period. However, the thrusts and thrust torque which were generated in the simulation for the three cases are quite reasonable in size. The control efforts with PAA vary within approximately ±15% of the control efforts without PAA at each time step.

The initial values of the controller, described previously in 3), were roughly estimated from the linearized vehicle equations about the desired steady state vehicle velocities with parameters of case 1, which might be considered as a base case in the simulation. It is rather difficult to estimate exact or near-optimum values of the system parameters for the general case even with an expensive hydrodynamic test on the actual ROV system since the ROV is a nonlinear, time-varying system dependent on the current and payload as discussed in section II. Therefore, even though the initial values for the controller were estimated with parameters of case 1, they are rather arbitrary. Since the same initial values were used for both control systems with PAA and without PAA in the simulation, both control systems with and without PAA were implemented with the same initial misalignment of the controller gains in each case. The initial misalignment of the controller gains was well compensated by the PAA. However, when the PAA is not activated, the vehicle fails to keep the desired velocity resulting in a significant amount of steady error. Therefore, it can be easily noticed that perfor-
Fig. 6. Surging rate error (Case 2).

Fig. 7. Swaying rate error (Case 2).

Fig. 8. Heading rate error (Case 2).

Fig. 9. Surging rate error (Case 3).

Fig. 10. Swaying rate error (Case 3).

Fig. 11. Heading rate error (Case 3).
mance of the adaptive control system is barely dependent on initial conditions, while performance of the nonadaptive control system is highly dependent on initial conditions. The control strategy presented in this paper does not require the explicit expression of the ROV dynamic model. The results of case study show that the adaptive control scheme can provide robust control with respect to parameter uncertainties even though a simplified model (16) and (26) of the vehicle was used to design the control system.

V. CONCLUSION

In this paper, we have presented a dynamic model and an adaptive control system for ROVs. The ROV dynamic model is described by a set of six nonlinear, time-varying differential equations having poorly known parameters that may be identified by expensive hydrodynamic testing on the vehicle. Even with such a test, it is almost impossible to derive the complete dynamic model since these tests do not take into consideration any unsteady fluid motion effects. Also, the parameters of the dynamic model may vary with changes in the ROV configuration and the environment. Therefore, it is obvious to develop a robust control system with respect to parameter uncertainties.

The control strategy presented in this paper does not require a priori knowledge about the vehicle system parameters. The effectiveness of the presented adaptive control system was investigated in the case study. Without any change in the control system, the adaptive control system was implemented for three cases which have different values of system parameters and currents. The results were compared with the results obtained by using the nonadaptive control system (i.e. control system without PAA) implemented with the same initial conditions. The results of case study show that the presented adaptive control scheme can provide high performance in terms of speed and accuracy in the presence of uncertainties of the vehicle and its environment, while the nonadaptive control system cannot. Future research efforts on this subject include the experimental investigation on the approach presented in this paper, and the control system integration with computer vision.
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