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Adaptive control of underwater vehicle-manipulator systems using radial basis function networks

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Abstract: This paper deals with a control scheme for underwater vehicle-manipulator systems with the dynamics of thrusters in the presence of uncertainties in system parameters. We have developed a regressor-based adaptive and a robust controller that overcome thruster nonlinearities, which cause an uncontrollable system. However, the structure of the adaptive controller is very complex due to the feedforward terms including the regressors of dynamic system models, and the error feedback gains of the robust controller with a good control performance are excessively high due to the lack of feedforward terms. In this paper we develop an adaptive controller that uses radial basis function networks instead of the feedforward terms. The replacement leads to a moderately high gain controller whose structure is simpler than that of the regressor-based adaptive controller.

Keywords: adaptive control, radial basis function network, thruster dynamics, underwater vehicle-manipulator system

1 INTRODUCTION

Adaptive or robust control schemes for autonomous underwater vehicles with manipulators, referred to as underwater vehicle-manipulator system (UVMS), have recently been developed in the presence of uncertainties in system parameters [1, 2]. In a general type of UVMS, the vehicle is propelled by marine thrusters, whereas the manipulator is driven by electrical motors. Despite such a different actuator system, the existing control schemes in [1, 2] were designed based on the dynamic system models without the thruster dynamics to obtain a simply structured controller. In each control scheme, furthermore, a high gain control system is constructed in order to achieve a good control performance. However, the vehicle propelled by marine thrusters generally has a considerably slower time response than the manipulator driven by electrical motors [2], and hence the high gains may excite the ignored thruster dynamics, which degrades a control performance and may even cause instability.

In order to overcome the problem, we have developed a regressor-based adaptive controller for UVMS with the thruster dynamics [3]. The adaptive control inputs are composed of adaptive feedforward signals including the regressors of the dynamic system models, and error feedback signals. Since the slow thruster dynamics is taken into consideration in the controller development, the control performance can be improved by the high gain feedback terms. However, the structure of the adaptive controller is very complex due to the regressors. On the other hand, we have developed a robust controller where the adaptive term is removed completely [4]. Although it has a much simpler structure than that of the adaptive controller, the removal leads to an excessively high gain controller, which may cause saturation or oscillations in the control inputs, to achieve a good control performance.

In this paper we develop an adaptive controller that uses radial basis function (RBF) networks, a type of neural network, instead of the adaptive terms including the regressors (see Fig. 1). The replacement leads to a moderately high gain controller whose structure is simpler than that of the regressor-based adaptive controller [3].

2 UVMS MODEL

Consider an underwater vehicle equipped with a Dm link manipulator with revolute joints. Let Dv and De be the numbers of dimensions for the vehicle's and the manipulator end-effector's motions, respectively. We assume without loss of generality that $Dm = De$.

As in [1, 5], the mathematical model of a UVMS with thruster dynamics is expressed as

$$\left.\begin{aligned} M(\phi)\ddot{x}(t) + f(\phi, u) &= J(\phi)^{-T}\begin{bmatrix} \bar{R}(\phi)\bar{K}D(v)v(t) \\ \tau_m(t) \end{bmatrix} \\ \dot{v}(t) &= -\frac{1}{2}AD(v)v(t) + \frac{1}{2}B\tau_b(t) \end{aligned}\right\} \quad (1)$$

$$\left.\begin{aligned} M(\phi) &= J(\phi)^{-T}\bar{M}(\phi)J(\phi)^{-1} \\ f(\cdot) &= J(\phi)^{-T}[\bar{f}(\phi, u) - \bar{M}(\phi)J(\phi)^{-1}\dot{J}(\phi, u)u(t)] \\ D(v) &= \mathrm{diag}\{|v_1|, \dots, |v_{Dv}|\} \end{aligned}\right\} \quad (2)$$

where $D(\cdot) \in R^{Dv \times Dv}$, $v_i(t)$ is the ith element of $v(t)$, and the explanation of the main symbols is shown in Table 1.

In this paper, the backstepping control technology is used to develop an adaptive controller. To this end, the state $v(t)$ has to be replaced by the new one $z(t) = D(v)v(t)$. Rewriting the signal $D(v)v(t)$ as $z(t)$ in the model (1), we obtain the new representation

$$\left.\begin{aligned} M(\phi)\ddot{x}(t) + f(\phi, u) &= H(\phi)^T K\begin{bmatrix} z(t) \\ \tau_m(t) \end{bmatrix} \\ \dot{z}(t) &= -AD(v)z(t) + BD(v)\tau_b(t) \end{aligned}\right\} \quad (3)$$

$$\left.\begin{aligned} H(\phi) &= R(\phi)^T J(\phi)^{-1} \\ R(\phi) &= \begin{bmatrix} \bar{R}(\phi) & 0 \\ 0 & I_m \end{bmatrix}, \quad K = \begin{bmatrix} \bar{K} & 0 \\ 0 & I_m \end{bmatrix} \end{aligned}\right\} \quad (4)$$

where $R(\cdot),\ K \in R^{Dn \times Dn}$ and $I_m \in R^{Dm \times Dm}$ is an identity matrix.

The model (3) has the following properties useful for our controller development [1, 5]:

P1) The diagonal elements of A, B and $\bar{K}$ are positive constants, and there exists a positive constant c_B such that $c_B\|\bar{y}\|^2 \le \bar{y}^T B\bar{y}$ for any $\bar{y} \in R^{Dv}$.

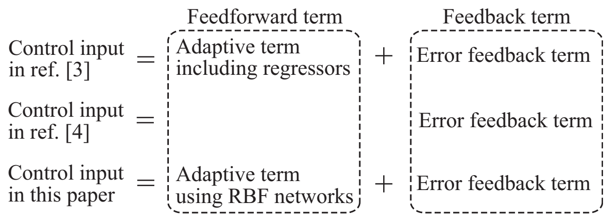

Fig. 1. Comparison of our controllers

Table 1. Symbols in the model (1)

Da	Number of dimensions for vehicle's orientation and manipulator's joint angles
Dn	Number of dimensions $Dv + De = Dv + Dm$
$x(t)$	Signal composed of vehicle's and manipulator end-effector's positions and orientations ($\in R^{Dn}$)
$\phi(t)$	Signal composed of vehicle's orientation and manipulator's joint angles ($\in R^{Da}$)
$u(t)$	Signal composed of vehicle's translational velocity and $\dot{\phi}(t)$ ($\in R^{Dn}$)
$\tau_m(t)$	Joint torques of manipulator ($\in R^{Dm}$)
$J(\phi)$	Jacobian matrix in the equation $\dot{x}(t) = J(\phi)u(t)$ ($\in R^{Dn\times Dn}$)
$\bar{R}(\phi)$	Transformation matrix from thrust forces to force and torque concerning inertial coordinate system ($\in R^{Dv\times Dv}$)
$\bar{M}(\phi)$	Inertia matrix ($\in R^{Dn\times Dn}$)
$\bar{f}(\cdot)$	Signal composed of centrifugal, Coriolis, gravitational and buoyant forces, and fluid drag ($\in R^{Dn}$)
$v(t)$	Shaft velocities of thruster's propellers ($\in R^{Dv}$)
$\tau_b(t)$	Shaft torques of thruster's propellers ($\in R^{Dv}$)
A, B, $\bar{K}$	Diagonal matrices composed of thruster's system parameters ($\in R^{Dv\times Dv}$)

P2) Each of $J(\phi)$ and $R(\phi)$ is composed of kinematic parameters and the functions of $\phi(t)$. Moreover, if each of $J(\phi)$ and $R(\phi)$ has a full rank, then there exists a positive constant c_{H2K} such that $c_{H2K}\|\bar{x}\|^2 \le \bar{x}^T H(\phi)^T K H(\phi)\bar{x}$ for any $\bar{x} \in R^{Dn}$.
P3) If $J(\phi)$ has a full rank, then $M(\phi)$ is symmetric and positive definite, and there exists a positive constant c_M such that $\|M(\phi)\| \le c_M$.

3 CONTROLLER DESIGN

The control objective is to develop a controller so that all the signals in the closed loop system can be bounded and the state $x(t)$ can track the desired trajectory $x_r(t)$ under the condition that the dynamic and hydrodynamic parameters (e.g., mass and a drag coefficient) are unknown constants.

In order to meet the objective, we make the following assumptions about the model (3) and the reference model (i.e., the desired trajectory $x_r(t)$):
A1) The signals $\phi(t)$, $x(t)$, $u(t)$ and $v(t)$ are available.
A2) The kinematic parameters in (3) (e.g., length) are known constants.
A3) Each of the matrices $J(\phi)$ and $R(\phi)$ in (3) has a full rank.
A4) The desired trajectory $x_r(t)$ and the derivatives $\dot{x}_r(t)$, $\ddot{x}_r(t)$ and $x_r^{(3)}(t)$ exist and are bounded.
It follows from the property P2 and the assumptions A1 and A2 that $J(\phi)$ and $R(\phi)$ are known matrices, and hence $\dot{x}(t)$ is available by using the equation $\dot{x}(t) = J(\phi)u(t)$.

In the following subsections we develop a controller that achieves the control objective by using a two-step backstepping procedure, as shown in Fig. 2. The first step is the design of an adaptive controller for the inputs $z(t)$ and $\tau_m(t)$, called Adaptive Controller I in this paper. The second step is the design of an adaptive controller for the input $\tau_b(t)$, called Adaptive Controller II in this paper. In this step we first replace $z(t)$, determined in the first step, by the desired trajectory $z_r(t)$, and then design the control input $\tau_b(t)$ so that $z(t)$ can track $z_r(t)$.

3.1 Adaptive Controller I

According to the design procedure shown in Fig. 2, we make the following assumption in the design of Adaptive Controller I:
A5) The control inputs are $z(t)$ for vehicle control and $\tau_m(t)$ for manipulator control.

In order to achieve the control objective described above, we use the tracking errors

$$\tilde{s}(t) = \dot{\tilde{x}}(t) + \alpha\tilde{x}(t), \quad \tilde{x}(t) = x(t) - x_r(t) \tag{5}$$

where $\alpha > 0$ is a constant design parameter. Using the first equations of (3) and (5), we have the error models

$$\left.\begin{aligned} M(\phi)\dot{\tilde{s}}(t) &= H(\phi)^T K\begin{bmatrix} z(t) \\ \tau_m(t)\end{bmatrix} - \frac{1}{2}\dot{M}(\cdot)\tilde{s}(t) \\ &\quad -H(\phi)^T K f_x(n_x) - \tilde{x}(t) \\ \dot{\tilde{x}}(t) &= -\alpha\tilde{x}(t) + \tilde{s}(t) \end{aligned}\right\} \tag{6}$$

$$\begin{aligned} f_x(n_x) = K^{-1}H(\phi)^{-T}\{f(\cdot) - \frac{1}{2}\dot{M}(\cdot)\tilde{s}(t) \\ -M(\phi)[\alpha\dot{\tilde{x}}(t) - \ddot{x}_r(t)] - \tilde{x}(t)\} \end{aligned} \tag{7}$$

where $n_x(\cdot) \in R^{5Dn+Da}$ is composed of $\phi(t)$, $x(t)$, $x_r(t)$, $\dot{x}_r(t)$, $\ddot{x}_r(t)$ and $u(t)$. In a subsequent analysis, the control input $z(t)$ will contain $n_x(t)$. Moreover, the time derivative of $z(t)$ (i.e., the time derivative of $n_x(t)$) will have to be used in the control input $\tau_b(t)$ of Adaptive Controller II. However, the signal $n_x(t)$ includes $u(t)$ whose time derivative is not directly available, and hence we divide $n_x(t)$ into $u(t)$ and $n_{x1}(t)$ composed of $\phi(t)$, $x(t)$, $x_r(t)$, $\dot{x}_r(t)$ and $\ddot{x}_r(t)$ whose time derivatives are directly available.

In this paper, the nonlinear term $f_x(n_x)$ in the error model (6) is replaced by the following RBF network and compensated by Adaptive Controller I:

$$f_x(n_x) = \Theta_x\omega_x(n_x) + \delta_x(n_x) \tag{8}$$

where $\Theta_x \in R^{Dn\times Dx}$ is a constant parameter, $\delta_x(n_x)$ is an approximation error, and $\omega_x(\cdot) \in R^{Dx}$ is a signal whose ith element is given by

$$\omega_{xi}(n_x) = e^{-\|n_x(t)-\bar{n}_{x1i}\|^2/\bar{n}_{x2i}^2} \tag{9}$$

where $\bar{n}_{x1i} \in R^{5Dn+Da}$ and $\bar{n}_{x2i} \in R$ are constant design parameters. In order to obtain an adequate approximation accuracy, the network dimensions Dx is chosen to be sufficiently high so that the following assumption can be satisfied:
A6) There exists a positive constant $c_{\delta x}$ such that $\|\delta_x(n_x)\| \le c_{\delta x}$ for any $n_x(\cdot) \in \bar{R}_x$, where $\bar{R}_x$ is a compact subset of R^{5Dn+Da}.
The assumption A6 is a reasonable assumption because it is shown in [6] that an RBF network can approximate any continuous function on a compact set.

The adaptive control law for the error model (6) subject to the assumptions A1 to A6 is given by

$$\begin{bmatrix} z(t) \\ \tau_m(t)\end{bmatrix} = \hat{\Theta}_x(t)\omega_x(n_x) - \alpha H(\phi)\tilde{s}(t) \tag{10}$$

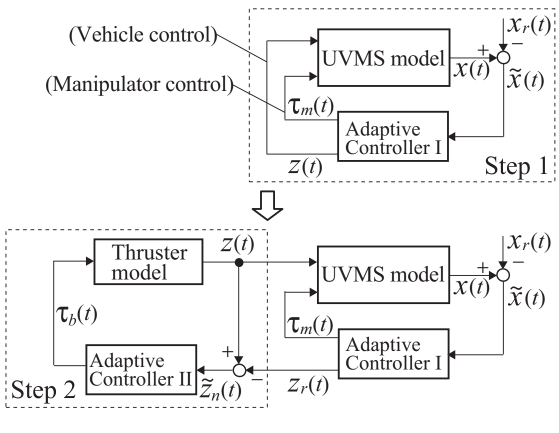

Fig. 2. Controller design procedure

where $\hat{\Theta}_x(t)$, the estimate of Θ_x, is generated by the adaptive law

$$\dot{\hat{\Theta}}_x(t) = -\sigma_{x1}\hat{\Theta}_x(t) - \sigma_{x2}H(\phi)\tilde{s}(t)\omega_x(n_x)^T \quad (11)$$

where $\sigma_{x1}, \sigma_{x2} > 0$ are constant design parameters. It can be shown that the adaptive controller (10) and (11) guarantees an ultimate boundedness of the tracking error $\tilde{x}(t)$.

3.2 Adaptive Controller II

According to the design procedure shown in Fig. 2, we make the following assumption instead of the assumption A5 in the design of Adaptive Controller II:

A7) The control inputs are $\tau_b(t)$ for vehicle control and $\tau_m(t)$ for manipulator control.

As shown in Fig. 2, we first replace the input $z(t)$ in (10) by the desired trajectory $z_r(t)$, i.e.,

$$\begin{bmatrix} z_r(t) \\ \tau_m(t) \end{bmatrix} = \hat{\Theta}_x(t)\omega_x(n_x) - \alpha H(\phi)\tilde{s}(t) \quad (12)$$

and then design Adaptive Controller II by using the tracking error of $z(t)$. When we choose the error as the normal one $\tilde{z}_n(t) = z(t) - z_r(t)$, the error model is written as $\dot{\tilde{z}}_n(t) = -AD(v)z(t) - \dot{z}_r(t) + BD(v)\tau_b(t)$. This model has a situation where the system is uncontrollable due to the lack of the rank of $BD(v)$ when some of $v_i(t)$ equal zero. This situation is caused by the thruster nonlinearities. In order to avoid the situation, we propose the following error instead of the normal one $\tilde{z}_n(t)$:

$$\tilde{z}(t) = z(t) - z_r(t) + \frac{2}{\epsilon}\, l(v) \quad (13)$$

$$\left.\begin{aligned} & l(v) = \{I_v - E(v)\}\,\bar{v}(v) \\ & E(v) = \mathrm{diag}\left\{e^{-|v_1|}, \ldots, e^{-|v_{Dv}|}\right\} \\ & \bar{v}(v) = [\mathrm{sgn}(v_1), \ldots, \mathrm{sgn}(v_{Dv})]^T \end{aligned}\right\} \quad (14)$$

where $\bar{v}(\cdot) \in R^{Dv}$, $E(\cdot) \in R^{Dv\times Dv}$, $I_v \in R^{Dv\times Dv}$ is an identity matrix, and $\epsilon > 0$ is a design parameter. It should be noted that $l(v)$ is bounded for all $v(t)$. As a result of adding the term $l(v)$, the error model of $\tilde{z}(t)$ is expressed as

$$\dot{\tilde{z}}(t) = BL(v)\tau_b(t) - Bf_z(n_z) - \bar{I}^T KH(\phi)\tilde{s}(t) \quad (15)$$

$$\left.\begin{aligned} & L(v) = D(v) + \frac{1}{\epsilon}E(v), \quad \bar{I} = \begin{bmatrix} I_v \\ 0 \end{bmatrix} \\ & f_z(n_z) = B^{-1}[AL(v)z(t) - \bar{I}^T KH(\phi)\tilde{s}(t) + \xi(t) \\ & \qquad + \bar{I}^T\{Y(\dot{u})y_2(t) - \alpha H(\phi)J(\phi)\dot{u}(t)\}] \\ & \xi(t) = \bar{I}^T\{y_1(t) + \dot{\hat{\Theta}}_x(t)\omega_x(n_x) - \alpha\dot{H}(\cdot)\tilde{s}(t) \\ & \qquad -\alpha H(\phi)[\dot{J}(\cdot)u(t) - \ddot{x}_r(t) + \alpha\dot{\tilde{x}}(t)]\} \\ & y_1(t) = -2\,\hat{\Theta}_x(t)\bar{Y}_1(n_x)\dot{n}_{x1}(t) \\ & y_2(t) = -2\begin{bmatrix} \bar{Y}_2(n_x)^T\hat{\theta}_{x1}(t) \\ \vdots \\ \bar{Y}_2(n_x)^T\hat{\theta}_{xDn}(t) \end{bmatrix} \\ & \bar{Y}_1(n_x) = \begin{bmatrix} \bar{\omega}_1(n_x)[n_{x1}(t) - \bar{n}_{x111}]^T \\ \vdots \\ \bar{\omega}_{Dx}(n_x)[n_{x1}(t) - \bar{n}_{x11Dx}]^T \end{bmatrix} \\ & \bar{Y}_2(n_x) = \begin{bmatrix} \bar{\omega}_1(n_x)[u(t) - \bar{n}_{x121}]^T \\ \vdots \\ \bar{\omega}_{Dx}(n_x)[u(t) - \bar{n}_{x12Dx}]^T \end{bmatrix} \\ & Y(\dot{u}) = \begin{bmatrix} \dot{u}(t)^T & & 0 \\ & \ddots & \\ 0 & & \dot{u}(t)^T \end{bmatrix}, \quad \bar{\omega}_i(n_x) = \frac{\omega_{xi}(n_x)}{\bar{n}_{x2i}^2} \end{aligned}\right\} \quad (16)$$

$$\hat{\Theta}_x(t) = \begin{bmatrix} \hat{\theta}_{x1}(t)^T \\ \vdots \\ \hat{\theta}_{xDn}(t)^T \end{bmatrix}, \quad \bar{n}_{x1i} = \begin{bmatrix} \bar{n}_{x11i} \\ \bar{n}_{x12i} \end{bmatrix} \quad (17)$$

where $\bar{I} \in R^{Dn\times Dv}$, $Y(\cdot) \in R^{Dn\times(Dn)^2}$, $\bar{n}_{x11i} \in R^{4Dn+Da}$, $\bar{n}_{x12i} \in R^{Dn}$, $\bar{Y}_1(\cdot) \in R^{Dx\times(4Dn+Da)}$, $\bar{Y}_2(\cdot) \in R^{Dx\times Dn}$, $\hat{\theta}_{xi} \in R^{Dx}$, and $\bar{\omega}_i \in R$. In the derivation of (15), we use the equation

$$\hat{\Theta}_x(t)\dot{\omega}_x(n_x, \dot{n}_x) = y_1(t) + Y(\dot{u})y_2(t), \quad (18)$$

which is modified so that $\hat{\Theta}_x(t)\dot{\omega}_x(\cdot)$ in $\dot{z}_r(t)$ can be separated into the unavailable signal $\dot{u}(t)$ and the available ones $y_1(t)$ and $y_2(t)$. It is noteworthy that the coefficient matrix $BL(v)$ of the input $\tau_b(t)$ in the error model (15) has a full rank for all $v(t)$, and hence the error model is controllable in spite of the thruster nonlinearities.

The nonlinear term $f_z(n_z)$ in the error model (15) is replaced by an RBF network in a way similar to the design of Adaptive Controller I. For the replacement of a function (e.g., $y = f(x)$) by an RBF network, it is necessary to identify not the structure but the arguments of a function replaced (i.e., x of $f(x)$). In view of the fact that the arguments of the unavailable signal $\dot{u}(t)$ are $\phi(t)$, $u(t)$, $v(t)$ and $\tau_m(t)$ (i.e., $\dot{u}(\phi, u, v, \tau_m)$), it can be seen from the third equation of (16) that the argument $n_z(t)$ of $f_z(n_z)$ is composed of $\phi(t)$, $u(t)$, $\tilde{s}(t)$, $v(t)$, $\tau_m(t)$, $y_2(t)$ and $\xi(t)$. The nonlinear term $f_z(n_z)$ is replaced by the following RBF network:

$$f_z(n_z) = \Theta_z\omega_z(n_z) + \delta_z(n_z) \quad (19)$$

where $\Theta_z \in R^{Dv\times Dz}$ is a constant parameter, $\delta_z(n_z)$ is an approximation error, and $\omega_z(n_z) \in R^{Dz}$ is a signal whose ith element is given by

$$\omega_{zi}(n_z) = e^{-\|n_z(t)-\bar{n}_{z1i}\|^2/\bar{n}_{z2i}^2} \quad (20)$$

where $\bar{n}_{z1i} \in R^{(Dn+3)Dn+Da+Dv}$ and $\bar{n}_{z2i} \in R$ are constant design parameters. We make the following assumption in common with the assumption A6:

A8) There exists a positive constant $c_{\delta z}$ such that $\|\delta_z(n_z)\| \le c_{\delta z}$ for any $n_z(\cdot) \in \bar{R}_z$, where $\bar{R}_z$ is a compact subset of $R^{(Dn+3)Dn+Da+Dv}$.

The adaptive control law for the error model (15) subject to the assumptions A1 to A4, A7 and A8 is given by

$$\tau_b(t) = L(v)^{-1}[\hat{\Theta}_z(t)\omega_z(n_z) - \alpha\tilde{z}(t)] \quad (21)$$

where $\hat{\Theta}_z(t)$, the estimate of Θ_z, is generated by the adaptive law

$$\dot{\hat{\Theta}}_z(t) = -\sigma_{z1}\hat{\Theta}_z(t) - \sigma_{z2}\,\tilde{z}(t)\omega_z(n_z)^T \quad (22)$$

where $\sigma_{z1}, \sigma_{z2} > 0$ are constant design parameters.

For Adaptive Controller I and II, the following theorem holds:

Theorem 1 Consider the adaptive controller (11), (12), (21) and (22) for the error models (6) and (15) subject to the assumptions A1 to A4 and A6 to A8. This controller guarantees that signals in the closed loop system are bounded, and that the tracking error $\tilde{x}(t)$ satisfies the inequality

$$\|\tilde{x}(t)\|^2 \le \rho_1\, e^{-\gamma\alpha t} + \frac{\rho_2}{\alpha^2\bar{\epsilon}} \quad (23)$$

where $\rho_1, \rho_2 > 0$ are positive constants, $\bar{\epsilon} = \min\{1, \epsilon^2\}$, and $\gamma = \min\{c_{H2K}/(2\,c_M), 1, c_B\}$.

Proof: We can prove Theorem 1 in a way similar to the proofs of the main theorems in [3,4].

4 SIMULATION EXAMPLE

In order to confirm the usefulness of the adaptive controller (11), (12), (21) and (22), we performed numerical simulations. Typical simulation results are presented in this paper. The UVMS simulated here was an underwater vehicle with a two-link manipulator, as shown in Fig. 3. The values of its system parameters (excepting thruster's parameters) were the same as those used in [3, 4]. In this figure, only the values of the main parameters are shown. The system parameters of the thrusters were given by $A = (1/T)I_3$, $B = (612.5/T)I_3$, $\bar{K} = 0.0408I_3$, where $I_3 \in R^{3\times3}$ is an identity matrix and T is a positive constant. These values were determined so that the steady state responses could be roughly the same as those of the experimental results in [7], whereas the transient responses are changed by the parameter T. It should be noted that the time responses of the thrusters become slower with an increase in the parameter T. The design parameters of the proposed adaptive controller were chosen as $\alpha = 100$, $\sigma_{x1} = \sigma_{z1} = 0.01$, $\sigma_{x2} = \sigma_{z2} = 1$, $\epsilon = 10$, $Dx = Dz = 50$, $\bar{n}_{x2i} = \bar{n}_{z2j} = 3$, $\hat{\Theta}_{xki}(0) = \hat{\Theta}_{zhj}(0) = 0$ where $\hat{\Theta}_{xki}(\cdot)$ and $\hat{\Theta}_{zhj}(\cdot)$ are the (k, i)th and the (h, j)th element of $\hat{\Theta}_x(\cdot)$ and $\hat{\Theta}_z(\cdot)$, respectively. In addition, the design parameters $\bar{n}_{x1i}$ and $\bar{n}_{z1j}$ were set as points into which the interval of each variable corresponding to $n_x(t)$ and $n_z(t)$ is divided equally. Each of the desired trajectories of the vehicle's and the manipulator end-effector's position was set up along a straight path. Each of the velocities was given by a filtered trapezoidal function. In these simulations, the time at which each of the desired trajectories reaches a target point was about 15 seconds. On the other hand, the desired trajectory of the vehicle's orientation is selected to remain at the initial value.

In order to investigate an effect of thruster dynamics on a control performance, we performed simulations using a controller for UVMS without thruster dynamics, called Static Controller in this paper. Static Controller is composed of (11), (12) and the static model $\tau_b(t) = B^{-1}Az_r(t)$, which is obtained from the second equation of (3) when $\dot{z}(t) = 0$. Figure 4 shows the tracking errors of Static Controller for $T = 0.01, 0.1, 1$. It is worth noting that an unstable robot motion was observed when $T > 1$. It can be seen from this figure that the tracking error increases with an increase in the parameter T. This means that a slow thruster dynamics degrades a control performance when Static Controller is used. On the other hand, Fig. 5 shows the tracking errors of the adaptive controller (11), (12), (21) and (22) for $T = 1, 10, 100$. As shown in this figure, the tracking errors are roughly the same and remain small in the three cases, irrespective of the parameter T.

In order to compare the proposed adaptive controller with the robust controller developed in [4], we performed simulations using the robust controller. Figure 6 shows the tracking errors of the adaptive and the robust controller for $T = 1$. It can be seen from this figure that the tracking error of the proposed adaptive controller is smaller than that of the robust controller. It is noteworthy that the steady state error of the adaptive controller is considerably reduced, particularly after the desired trajectories reach the target points.

5 CONCLUSION

In this paper we developed an adaptive controller for underwater vehicle-manipulator systems with thruster dynamics. In the controller development we presented a new tracking error model that overcomes uncontrollability caused by the thruster dynamics, and then designed the adaptive controller with radial basis function networks. Furthermore, the usefulness of the proposed controller was demonstrated by the simulation results.

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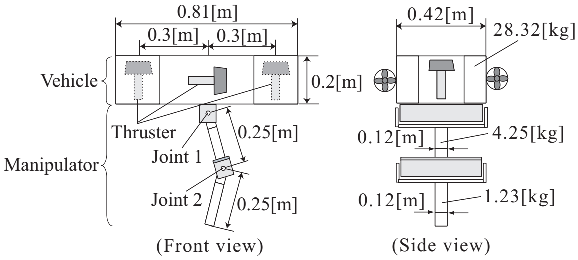

Fig. 3. UVMS for numerical simulation

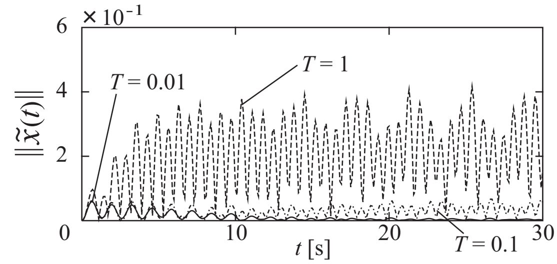

Fig. 4. Simulation results of Static Controller

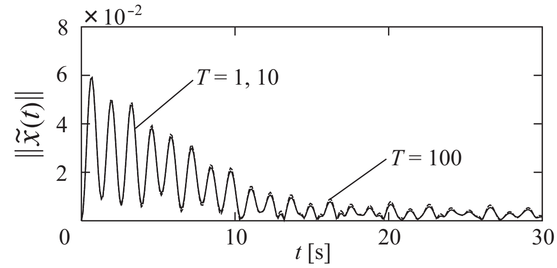

Fig. 5. Simulation results of proposed adaptive controller

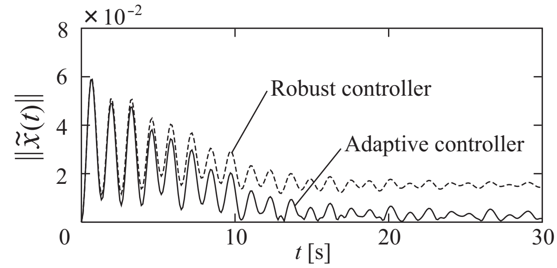

Fig. 6. Simulation results of controllers for $T = 1$

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