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NEURAL NETWORK CONTROLLER FOR MANIPULATION OF MICRO-SCALE OBJECTS

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***Abstract*—In this paper, a novel reinforcement learning-based neural network (RLNN) controller is presented for the manipulation and handling of micro-scale objects in a micro-electromechanical system (MEMS). In MEMS, adhesive, surface tension, friction and van der Waals forces are dominant. Moreover, these forces are typically unknown. The RLNN controller consists of an action NN for compensating the unknown system dynamics, and a critic NN to tune the weights of the action NN. Using the Lyapunov approach, the uniformly ultimate boundedness (UUB) of the closed-loop tracking error and weight estimates are shown by using a novel weight updates. Simulation results are presented to substantiate the theoretical conclusions.**

I. Introduction

MICRO-electromechanical system (MEMS) is a relatively new technology involving miniaturization of systems and components to create complex machines that are of micron size in nature. These are used in a variety of applications involving sensing, actuation and communication. The MEMS has revolutionized a major part of the sensor and actuator industry. Modeling of such micro-scale devices for actuation is a whole lot different from that in macro scale system. At micro scale, surface forces are predominant while volumnic forces are negligible [1]. The dominant forces acting on a MEMS system are adhesive, electrostatic and van der Waals forces, while the forces due to gravity are negligible. There are a lot of uncertainties, for instance fabrication imperfections and complex system nonlinearities, which make the actuation and manipulation of such devices difficult. Designing controllers for the manipulation and handling of micro-scale objects poses a much greater challenge in terms of accommodating the nonlinearities in the system. Hence, these forces have to be modeled in order to design a controller for the micro system. To confront some of the issues of nonlinearities and uncertainties in such MEMS systems, a reinforcement learning-based NN (RLNN) controller is designed. The RLNN structure allows coping with myriad variables in parallel, in real time, and in a noisy nonlinear environment [10], [11]. Furthermore, complex optimization problems can be realized in the RLNN structure. In the paper, the RLNN structure consists of two NNs: an action NN for compensating the uncertain nonlinear system dynamics, and a critic NN for tuning the weights of the action NN. A novel utility function, which is viewed as the system performance index over time, was defined as the critic NN input. The critic signal provides an additional corrective action based on current and past system performance. This information along with the filtered tracking error is used to tune the action NN.

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II. Modeling

Manipulation and handling of micro-scale objects are required for the assembly and maintenance of micro machines and their parts. In this study, we consider the manipulation of micro-sized spheres 50 μm in diameter. When manipulating objects in the micro domain, the micro-physics of the problem must be taken into account [2], [3]. Modeling is necessary for picking up micro-spheres laying on a planar substrate. The micro-sphere is to be picked up and it needs to be placed at another location for assembly or maintenance. The probe, which is treated as the end-effector and manipulator, is lowered to make contact with the micro-sphere. Once contact has been established, the probe is to be retracted and the micro-object has to be picked up due to the adhesive forces [4]. The process of placing the micro-object after it has been picked- up is also an intricate process. For the purpose of designing a controller for the object-handling task, we shall restrict ourselves with the intricacies of the physics of the picking up process as shown in Fig. 1. Hence, the adhesion forces are dominant in the system. Adhesive forces considered to play an important role in the manipulation process are:

- Van der Waals forces,
- Electrostatic forces (or coulomb) and
- Surface tension (or capillary) forces.

Materials and object geometries greatly decide the magnitude of Van der Waals forces. According to [4] the Van der Waals forces $F_{xx}^{\overline{VdW}}$, for an ideal geometry are given by

$$F_{xx}^{\overline{VdW}} = \frac{A_{xx}^{w} R_b}{6D_{xx}^2}, \qquad (1)$$

where the subscript xx stands for interactions at the ball-probe (bp) and ball-substrate (bs) interface. R_b is the radius of the sphere, A_{xx}^{w} is the Hamaker constant of "ball-water-surface/probe" interface, and D_{xx} is the separation distances. Van der Waals forces are also influenced by the surface roughness [2]. It has been shown that increasing the surface roughness decreases the Van der Waals forces [4].

Taking the surface roughness into consideration as shown in Fig. 2, the Van der Waals force F_{xx}^{VdW}, is given by

$$F_{xx}^{VdW} = \left(\frac{D_{xx}}{D_{xx} + b/2} \right)^2 F_{xx}^{\overline{VdW}}, \tag{2}$$

where b is the height of the surface irregularities (0.1 μm).

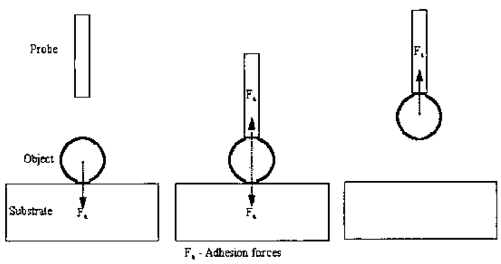

Fig. 1. Object handling task.

The capillary or surface tension force F_{xx}^{cap}, is expressed by

$$F_{xx}^{cap} = \frac{4\pi\gamma R_b d}{d + D_{xx}}, \tag{3}$$

where γ is the surface tension and d is the depth of immersion respectively.

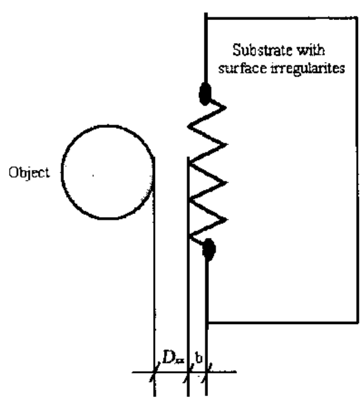

Fig. 2. Rough plate and plane sphere.

The electrostatic force F_{xx}^{elec}, between the ball-surface/probe interface is given by

$$F_{xx}^{elec} = \varepsilon_0 \pi \bar{d}^2 \left(\frac{3\varepsilon_1}{\varepsilon_1 + 2} \right)^2 E^2, \tag{4}$$

where ε_0 and ε_1 are the dielectric constants of free-space and the material, $\bar{d}$ is the reduced diameter obtained as $\bar{d} = \frac{2R_b d_x}{2R_b + d_x}$, where, d_x is the diameter of the irregularities of the surface/probe tip [2]. The parameter, E, is the voltage between the probe and the substrate. It has also been shown that the electrostatic forces can be minimized by applying an external voltage.

III. Dynamic Model

A dynamic model of the micro-scale object handling system is formulated considering all the forces mentioned above [4], [7]. The objects considered in this work include micro-spheres of diameter 50 to 200 μm (radius R_b varies from 25 μm to $100 \mu m$).

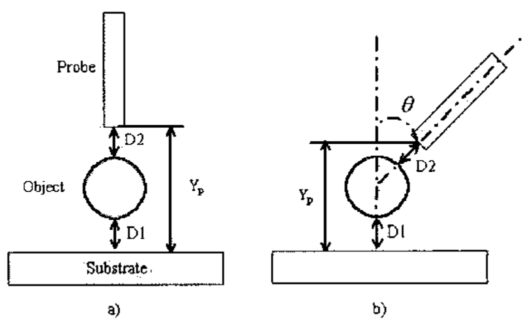

Fig. 3. Intersurfacic distances notation a) capture at straight and b) capture at an inclination.

The dynamic model for the object handling task is given by [4]:

$$m_p \ddot{Y}_p = F_{ext} \cos(\frac{\pi}{2} - \theta) - F_{bp}^{VdW} \cos\theta$$
$$- F_{bp}^{cap} \cos\theta - F_{bp}^{elec} \cos\theta - m_p g, \tag{5}$$

$$m_b \ddot{D}_1 = (F_{bp}^{VdW} + F_{bp}^{cap} + F_{bp}^{elec}) \cos\theta$$
$$- F_{bs}^{VdW} - F_{bs}^{cap} - F_{bs}^{elec} - m_b g, \tag{6}$$

$$Y_p = D_1 + R_b + (R_b + D_2) \cos\theta, \tag{7}$$

where, $\ddot{Y}_p$ is the probe acceleration, F_{ext} is the control force applied to the probe, θ is the angle of inclination of the probe with the vertical axis, F_{xx}^{VdW} is the Van der Waals forces, F_{xx}^{cap} is the capillary forces and F_{xx}^{elec} is the electrostatic forces for the ball-probe (bp) and the ball-substrate (bs) interfaces presented in (1) through (8) respectively. There are two constraints for this model

- $D_1 = 0.4nm \Rightarrow \ddot{D}_1 \geq 0$ (8)

when the ball contacts the substrate i.e. $D_1 = D_0 = 0.4nm$ and

- $F_{ext} > 2R_b \pi W_{ball-water-substrate}$, (9)

a detachment constraint expressed where $W_{ball-water-substrate}$ is the surface work of adhesion. The manipulation time has to be small to prevent ball substrate deformation. The dynamic model for the manipulation and handling of micro-scale objects are quite nonlinear and unknown. For instance, the surface tension, Hamaker constant, electric charge density, diameter of the object, height of immersion and so on are nonlinear and dynamically changing. Under these circumstances, one has to apply advanced control schemes in order to manipulate such micro-scale objects. The control scheme must guarantee object manipulation in the event of such unknown uncertainties.

IV. CONTROLLER DESIGN

The controller design proposed in this paper is based on the filtered tracking error formulation. The error system formulation along with the neural network controller structure has been discussed in detail in [4-5]. For the purpose of controller design, θ is considered as constant.

A. Filtered Tracking Error-Based Control Design

The manipulation and handling of the sphere is done when D_1 increases and $D_2 = D_0$ (atomic contact distance). Differentiating (8), to get

$$\dot{Y}_p = \dot{D}_1 + \dot{D}_2 \cos\theta, \quad (10)$$

and

$$\ddot{Y}_p = \ddot{D}_1 + \ddot{D}_2 \cos\theta, \quad (11)$$

or

$$\ddot{D}_2 = \frac{1}{\cos\theta}(\ddot{Y}_p - \ddot{D}_1), \quad (12)$$

Let the error e between the desired and the target position be defined as

$$e = D_2 - D_0. \quad (13)$$

Thus, when the error goes to zero, then $D_2 = D_0$ and the probe picks up the micro-sphere. Differentiating (13) to get:

$$\dot{e} = \dot{D}_2, \quad (14)$$

and

$$\ddot{e} = \ddot{D}_2 = \frac{1}{\cos\theta}(\ddot{Y}_p - \ddot{D}_1), \quad (15)$$

Let r be the filtered tracking error which is defined as,

$$r = \dot{e} + \Lambda e, \quad (16)$$

where $\Lambda \in R$ is a positive design parameter.

Differentiating (16) to get

$$\dot{r} = \ddot{e} + \Lambda \dot{e}, \quad (17)$$

Substituting for $\ddot{e}$ and $\dot{e}$ from (15) and (14) results in

$$\dot{r} = \frac{1}{\cos\theta}(\ddot{Y}_p - \ddot{D}_1) + \Lambda \dot{D}_2 = (F(Y_p) - F(D_1)) + \Lambda \dot{D}_2 + v, \quad (18)$$

where

$$F(Y_p) = \frac{1}{m_p}(-F_{bp}^{VdW} - F_{bp}^{cap} - F_{bp}^{elec} - \frac{1}{\cos\theta} m_p g), \quad (19)$$

and

$$F(D_1) = \frac{1}{m_b}(F_{bp}^{VdW} + F_{bp}^{cap} + F_{bp}^{elec}) - \left(F_{bs}^{VdW} + F_{bs}^{cap} + F_{bs}^{elec} + m_b g\right)\frac{1}{m_b \cos\theta}, \quad (20)$$

and v is the control input given by

$$v = \frac{1}{m_p \cos\theta} F_{ext} \cos(\pi/2 - \theta) = \frac{\tan\theta}{m_p} F_{ext}, \quad (21)$$

or

$$\dot{r} = F(X) + \Lambda \dot{D}_2 + v, \quad (22)$$

where $F(X) = F(Y_p) - F(D_1)$ is an unknown nonlinear function.

An action NN is employed to approximate this unknown system dynamics. According to [12], a single layer NN can be used to approximate any nonlinear continuous function over the compact set when the input layer weights are selected at random and held constant whereas the output layer weights are only tuned provided sufficiently large number of nodes in the hidden-layer is chosen. Therefore, a single layer NN is employed here whose output is defined as $\hat{w}_1^T \varphi(v_1^T X)$, where $\hat{w}_1 \in R^{n_1}$ and $v_1 \in R^{4 \times n_1}$ are the output and input layer weights, n_1 is the number of the hidden layer nodes, $\varphi(\cdot)$ is the activation function vector, and $X = [Y_p, D_2, \dot{Y}_p, \dot{D}_2]^T \in R^4$ is the input to the neural network. For simplicity, the output of the action NN is expressed:

$$\hat{F}(X) = \hat{w}_1^T \varphi(X). \quad (23)$$

Thus, a control input can be selected as

$$v = -\hat{F}(X) - \Lambda \dot{D}_2 - k_v r, \quad (24)$$

where $k_v \in R$ is the feedback gain.

Applying (24) in (22) to get

$$\dot{r} = -k_v r + \left(F(X) - \hat{F}(X)\right), \quad (25)$$

or

$$\dot{r} = -k_v r + \tilde{F}(X), \quad (26)$$

where $\tilde{F}(X) = F(X) - \hat{F}(X)$ is the function approximation error. When the neural network is properly trained and $\hat{F}(X)$ is an accurate estimate of $F(X)$, then $\tilde{F}(X) \to 0$ and (26) becomes

$$\dot{r} = -k_v r . \qquad (27)$$

If k_v is properly selected, then from (27) and (16) one can see that $e \to 0$ with $t \to \infty$. Thus, $D_2 = D_0$ and the sphere is said to be manipulated (pick-up task).

The unknown function $F(X)$ can be approximated by the action NN as

$$F(X) = w_1^T \varphi(v_1^T X) + \varepsilon(X) = w_1^T \varphi(X) + \varepsilon(X), \qquad (28)$$

where $w_1 \in R^{n_1}$ is the target output layer weight, and $\varepsilon(X)$ is the NN approximation error. Define the weight estimation error $\tilde{w}_1 \in R^{n_1}$ by

$$\tilde{w}_1 = w_1 - \hat{w}_1, \qquad (29)$$

Thus (25) becomes

$$\dot{r} = -k_v r + \tilde{w}_1^T \varphi(X) + \varepsilon(X). \qquad (30)$$

B. Design of the Critic NN.

The input to the critic NN is chosen as

$$z(t) = \int_0^t r^2(\tau) d\tau, \qquad (31)$$

A choice of the critic NN signal is given by

$$R(t) = \hat{w}_2^T \sigma(v_2^T z(t)) = \hat{w}_2^T \sigma(z(t)), \qquad (32)$$

where $\hat{w}_2 \in R^{n_2}$ and $v_2 \in R^{n_2}$ are the output and input layer weights, n_2 is the number of the hidden layer nodes, $\sigma(\cdot)$ is the hidden layer activation function vector, and $z(t) \in R$ is the input to the neural network. The critic NN input defines the long term system performance over time. The critic signal, $R(t)$, provides an additional corrective action based on current and past performance. This information along with filtered tracking error is used to tune the action NN. The critic signal can also be viewed as a look-ahead factor, which is determined based on past performance. The proposed reinforcement learning-based NN controller structure is depicted in Fig. 4. The next step is to determine the weight updates so that the performance of the closed-loop tracking error dynamics is guaranteed.

C. Main Result.

Assumption 1: The desired trajectory D_0 is bounded so that $|D_0| < D_B$ with D_B a known scalar bound. In fact, D_0 becomes the inter-atomic distance.

Assumption 2: The NN approximation error $\varepsilon(X)$ is bounded above by $|\varepsilon(X)| < \varepsilon_N$ over the compact set.

Assumption 3: Both the ideal weights and the activation functions for all NNs are bounded by known positive values so that

$$\|w_1\| \le w_{1\max}, \ \|w_2\| \le w_{2\max}, \qquad (33)$$

and

$$\|\sigma(\cdot)\| \le \sigma_{\max}, \ \|\varphi(\cdot)\| \le \varphi_{\max}. \qquad (34)$$

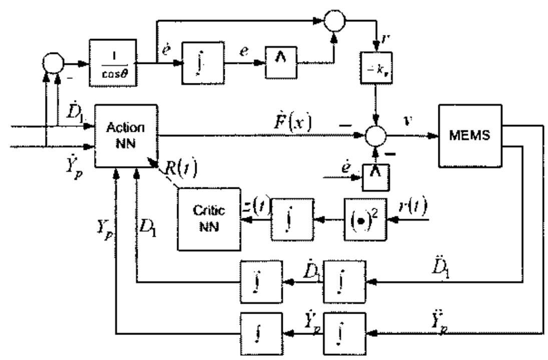

Fig. 4. Structure of the NN controller.

Theorem 1: Consider the system given in (5), (6) and (7), and take the Assumptions 1, 2 and 3. Let the action NN weights tuning be given by

$$\dot{\hat{w}}_1 = \varphi(X)(r - \hat{w}_1^T \varphi(X) + k_1 R(t)), \qquad (35)$$

where k_1 is a design parameter and $R(t)$ is the critic signal, which is given by the critic NN in (32). The critic NN weights be tuned by

$$\dot{\hat{w}}_2 = -\sigma(X)(r + R(t)), \qquad (36)$$

with the control signal selected by (24). The filtered tracking error r and the NN weights estimates, $\hat{w}_1$ and $\hat{w}_2$, are *UUB*, with the bounds specifically given by (A.10) through (A.12) provide the design parameters are selected as:

$$(1)\ k_v > \frac{1}{2}, \qquad (37)$$

$$(2)\ 1 > k_1 > 0. \qquad (38)$$

Proof: See Appendix.

V. Simulation

The purpose of the controller is to provide a control force for the probe to pick up the micro-object. It is assumed that the object is in contact with the substrate before it is picked up by the probe. The controller determines the magnitude of control force required for the capture of the micro-object at the tip of the end-effector. The controller provides the force to cause the actual capture and to retain the micro-sphere at the tip of the probe. Once the capture occurs, and the external force to be applied through the probe is determined and maintained to keep the micro-sphere captured. A PD controller is designed based on the filtered tracking error. Fig. 5 shows the distances for a proportional controller ($k_v = 5, \Lambda = 10^{-3}$). Fig. 6 shows the control input, which appears to be highly oscillatory. It takes a considerable amount of time to capture the micro-sphere. Fig. 7 shows the distances and Fig. 8 shows the control input resulting from using an reinforcement learning-based controller ($k_v = 5, \Lambda = 10^{-3}, k_1 = 0.8$). It can be seen that capture occurs around 10^{-3} s.

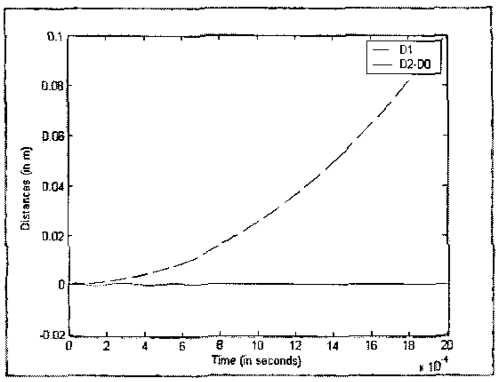

Fig. 5. Displacement using the PD controller.

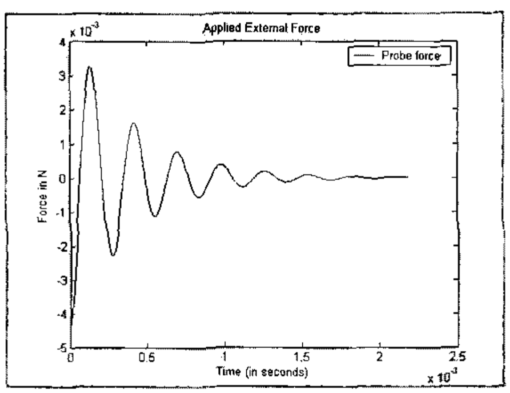

Fig. 6. Applied external force.

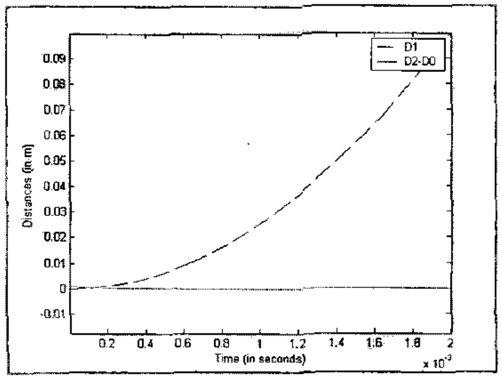

Fig. 7. Displacement with the NN controller.

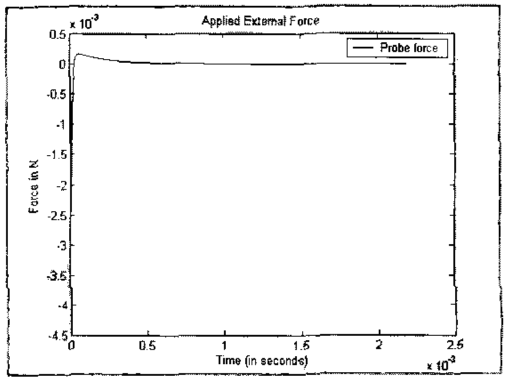

Fig. 8. The control input associated with the NN controller.

VI. Conclusion

A reinforcement learning-based NN controller has been developed for the task of picking up a micro-sphere from a substrate. The NN controller has been proven to have guaranteed stability. The task of manipulation has been possible even when the nonlinearities and uncertainties are not modeled for. It was found that the random selection of weights resulted in higher learning times. Pre-training of the neural network would help improve the speed of learning and manipulation.

Appendix

Proof of Theorem 1: Since $\dot{\tilde{w}}_1 = -\dot{\hat{w}}_1$, the updating rules (35) can be rewritten as

$$\begin{aligned}\dot{\tilde{w}}_1 &= \varphi(X)\left(-r + \hat{w}_1^T \varphi(X) - k_1 R(t)\right) \\ &= \varphi(X)\left(-r - \bar{e}_1 + w_1^T \varphi(X) + k_1 \tilde{w}_2^T \sigma(z(t)) - k_1 w_2^T \sigma(z(t))\right) \\ &= \varphi(X)\left(-r - \bar{e}_1 + k_1 \bar{e}_2 + \eta_1 - k_1 \eta_2\right) \ , \end{aligned} \qquad (A.1)$$

where

$\bar{e}_1 = \tilde{w}_1^T \varphi(X)$, $\bar{e}_2 = \tilde{w}_2^T \varphi(X)$, $\eta_1 = w_1^T \varphi(X)$ and

$$\eta_2 = w_2^T \sigma(z(t)). \quad (A.2)$$

Similarly, (36) can be rewritten as

$$\dot{\tilde{w}}_2 = \sigma(z(t))(r - \bar{e}_2 + \eta_2). \quad (A.3)$$

The Lyapunov function candidate is defined as

$$V = \frac{1}{2}\left(r^2 + \tilde{w}_1^T \tilde{w}_1 + \tilde{w}_2^T \tilde{w}_2\right). \quad (A.4)$$

Differentiating (A.4) to get

$$\dot{V} = r\dot{r} + \tilde{w}_1^T \dot{\tilde{w}}_1 + \tilde{w}_2^T \dot{\tilde{w}}_2. \quad (A.5)$$

Substitution of (30), (A.1) and (A.3) into (A.5)

$$\begin{aligned} \dot{V} &= r\left(-k_v r + \tilde{w}_1^T \varphi(X) + \varepsilon(X)\right) \\ &+ \tilde{w}_1^T \varphi(X)\left(-r - \bar{e}_1 + k_1 \bar{e}_2 + \eta_1 - k_1 \eta_2\right) \\ &+ \tilde{w}_2^T \sigma(z(t))(r - \bar{e}_2 + \eta_2) \\ &\le \left(-k_v r^2 + r\varepsilon(X) + \frac{1}{2}\left(r^2 + \bar{e}_2^2\right)\right) + \left(-\bar{e}_2^2 + \bar{e}_2 \eta_2\right) \\ &+ \left(-\bar{e}_1^2 + \frac{1}{2}k_1\left(\bar{e}_1^2 + \bar{e}_2^2\right) + \bar{e}_1\left(\eta_1 - k_1 \eta_2\right)\right) \end{aligned} \quad (A.6)$$

Simplify (A.6) to get

$$\begin{aligned} \dot{V} &\le -\frac{1}{2}(2k_v - 1)r^2 + r\varepsilon(X) - \frac{1}{2}(2 - k_1)\bar{e}_1^2 + \bar{e}_1(\eta_1 - k_1 \eta_2) \\ &- \frac{1}{2}(1 - k_1)\bar{e}_2^2 + \bar{e}_2 \eta_2 \end{aligned} \quad (A.7)$$

Complete the square to get

$$\begin{aligned} \dot{V} &\le -\frac{1}{2}(2k_v - 1)\left(r - \frac{\varepsilon(X)}{(2k_v - 1)}\right)^2 \\ &- \frac{1}{2}(2 - k_1)\left(\bar{e}_1 - \frac{(\eta_1 - k_1 \eta_2)}{(2 - k_1)}\right)^2 \\ &- \frac{1}{2}(1 - k_1)\left(\bar{e}_2 - \frac{\eta_2}{(1 - k_1)}\right)^2 + D^2 \end{aligned} \quad (A.8)$$

where

$$D^2 \le D_{\max}^2 = \frac{1}{2}\left(\frac{\varepsilon_N^2}{(2k_v - 1)} + \frac{2\left(w_{1\max}^2 \varphi_{\max}^2 + w_{2\max}^2 \sigma_{\max}^2\right)}{2 - k_1} + \frac{w_{2\max}^2 \sigma_{\max}^2}{2 - k_1}\right) \quad (A.9)$$

This further implies that the $\dot{V} < 0$ as long as (37) and (38) hold and

$$|r| > \frac{\varepsilon_N}{(2k_v - 1)} + \frac{\sqrt{2}D_{\max}}{\sqrt{2k_v - 1}}, \quad (A.10)$$

or

$$|\bar{e}_1| > \frac{w_{1\max}\varphi_{\max} + k_1 w_{2\max}\sigma_{\max}}{(2 - k_1)} + \frac{\sqrt{2}D_{\max}}{\sqrt{2 - k_1}}, \quad (A.11)$$

or

$$|\bar{e}_2| > \frac{w_{2\max}\sigma_{\max}}{(1 - k_1)} + \frac{\sqrt{2}D_{\max}}{\sqrt{1 - k_1}}, \quad (A.12)$$

According to a standard Lyapunov extension theorem [9], this demonstrates that the filtered tracking error and the error in weight estimates are UUB. The boundedness of $|\bar{e}_1|$ and $|\bar{e}_2|$ implies that $\|\tilde{w}_1\|$ and $\|\tilde{w}_2\|$ are bounded, and this further implies that the weight estimates $\hat{w}_1$ and $\hat{w}_2$ are bounded.

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