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Gustavo Galan

Jagannathan Sarangapani
Missouri University of Science and Technology, sarangap@mst.edu

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Adaptive Critic Neural Network-Based Object Grasping Control Using a Three-Finger Gripper

S. Jagannathan, *Senior Member, IEEE,* and Gustavo Galan

Abstract—**Grasping of objects has been a challenging task for robots. The complex grasping task can be defined as object contact control and manipulation subtasks. In this paper, object contact control subtask is defined as the ability to follow a trajectory accurately by the fingers of a gripper. The object manipulation subtask is defined in terms of maintaining a predefined applied force by the fingers on the object. A sophisticated controller is necessary since the process of grasping an object without *a priori* knowledge of the object's size, texture, softness, gripper, and contact dynamics is rather difficult. Moreover, the object has to be secured accurately and considerably fast without damaging it.**

Since the gripper, contact dynamics, and the object properties are not typically known beforehand, an adaptive critic neural network (NN)-based hybrid position/force control scheme is introduced. The feedforward action generating NN in the adaptive critic NN controller compensates the nonlinear gripper and contact dynamics. The learning of the action generating NN is performed on-line based on a critic NN output signal. The controller ensures that a three-finger gripper tracks a desired trajectory while applying desired forces on the object for manipulation. Novel NN weight tuning updates are derived for the action generating and critic NNs so that Lyapunov-based stability analysis can be shown. Simulation results demonstrate that the proposed scheme successfully allows fingers of a gripper to secure objects without the knowledge of the underlying gripper and contact dynamics of the object compared to conventional schemes.

Index Terms—**Adaptive controller, adaptive critic, neural networks (NNs), object grasping, three-finger gripper.**

I. INTRODUCTION

ANY planetary exploration to Mars is considered a long-duration mission. Therefore, before any human mission, NASA plans to construct a greenhouse on Mars equipped with autonomous robots to perform complex tasks such as harvesting wheat, rice, fruits, and vegetables, besides cleaning, cooking, and so on. *Grippers* capable of manipulating objects such as *plant trays, fruits, and vegetables* are required in the greenhouse. In order to manipulate objects, contact with the object has to be made and suitable grasping forces have to be applied. For successful manipulation, suitable grasping forces have to be determined without the knowledge of the type of object to be secured by the gripper.

Human fingers manipulate objects by using adequate forces even when the weight and the friction coefficient of the object

contact are unknown. Further, human fingers use tactile sensing to feel the texture of the object so that the required forces can be applied to manipulate the object without any slippage. Based on grasping operations typically performed by humans, several methods [1], [3], [4], [7]–[10] have been proposed for robot grippers. These methods involve making contact with the object at the right location and orientation by traveling along a predefined path by assuming that the properties of the object are known accurately.

Designing grippers to perform the grasping of objects of different shape, size, and texture is a complex and expensive task since the manipulating forces cannot be accurately determined. To minimize the complexity and cost, most of the designs rely on feeding the robot with a variety of possible object patterns. The position of the object relative to the gripper, its weight, orientation, and shape are specified beforehand. Using this information, the gripper is guided through a predefined trajectory to reach and to grasp the object with the proper force, while the integrity of the object is guaranteed throughout the manipulation. If the applied force is not sufficient, then the object can slip whereas too much applied force can destroy the object. Moreover, for successful manipulation, the fingers of a gripper have to make contact with the object at the right location and orientation to avoid slippage.

Securing an object can be summarized in three steps: 1) defining a trajectory for the arm to position the gripper around the object, 2) defining another trajectory for the fingers to make contact with the object at the right location and orientation, and 3) applying suitable forces on the object for manipulation. Even though the objects to be manipulated in a greenhouse can be described, the object properties cannot be determined. Further, even when the object weight and shape are known, the contact dynamics can be still unknown. Moreover, it is not practically viable to change grippers based on weight, size, shape, and texture of the object. Therefore, a sophisticated controller design without using the size, weight, texture, and contact dynamics is necessary for manipulating objects. Thus, designing a learning controller is of paramount importance for the greenhouse operation since the controller scheme has to ensure that the fingers make good contact and they apply the required forces on the object to avoid slippage without the knowledge of the properties of the object such as texture, weight, and contact dynamics.

One of the problems endured in grasping an object is the ability of the gripper to reach an object in different positions and orientations [4], [10]. For every time the object's location and orientation varies, a new trajectory for the gripper must

be computed. This problem is similar to a conventional trajectory-tracking problem in robot manipulators using vision feedback and, therefore, it is omitted in this paper. However, once the gripper is positioned around the object, a trajectory is computed for the fingers to make contact with the object and to apply the required forces for manipulation. Given the predefined trajectory, the robot's gripper controller has to respond accurately to every new path it is planned for [4], [10].

Since the selection of grasping forces based on the properties of an object is a challenging task, a neuro-fuzzy scheme may be designed to address this problem by using certain *a priori* information but this is not attempted. Instead, by performing detailed experiments in the laboratory, suitable forces are identified based upon the type of object. The grasping controller then has to ensure that the predefined forces are applied on the object for manipulation without causing any damage to the object.

Several techniques have been developed to identify and grasp objects using robot grippers. Novel concepts such as visual recognition [1], object avoidance [10], moving targets [10], switching control [7], grasp quality measures [8], force feedback [9], and force control [3] were proposed. Such techniques determine an adequate trajectory for the gripper to reach and grasp an object. However, the controllers presented in [1], [7]–[9] are either heuristic in nature or focus on object recognition [1]. No viable controller scheme to grasp an object in the presence of uncertainties is available in the literature.

For grasping tasks, the texture of the object can be described to some extent based on the contact friction dynamics. Subsequently, the required forces can be calculated based on the weight and the type of object. It is assumed that a vision feedback is available to identify the type of object and its approximate weight so that a desired force can be selected for grasping. It is also assumed that the gripper will be at correct position and orientation around the object before making contact with the object. Even if the above information is supplied to a controller, uncertainties still exist in terms of contact dynamics and the object weight.

Therefore, this paper presents the design of a hybrid position/force controller with online learning feature to enable the fingers of a robot gripper track the planned path not only to make contact with the object, but also to apply the predefined forces. Further, as it is very difficult to determine the texture and hence the contact dynamics beforehand in most grasping applications, this learning controller must guarantee performance in the presence of uncertainties.

Neural networks (NNs) have been shown to be a very effective tool for the control of nonlinear dynamical systems when the system/environment dynamics are not completely known. In reinforcement learning or adaptive critic-based NN [2] method, the learning is performed based on a performance measure from a critic NN instead of gradient information supplied to the NN using the backpropagation algorithm. In other words, the output provided by the critic NN conveys much less information than the desired output required in supervised learning. Nevertheless, their ability to generate correct control actions makes adaptive critics important candidates where a lack of sufficient structure in the task definition makes it difficult to define *a priori* the desired outputs for each input, as required by supervised

learning control [2]. In our scenario, where the desired outputs are the gripper and the contact dynamics, which are considered unknown, a supervised learning scheme cannot be utilized for training an NN.

In this paper, a novel adaptive critic NN-based gripper controller is developed for grasping objects. The action generating NN in the adaptive critic approximates the dynamics of the gripper and the contact so that the object can be approached and manipulated with the required force without damaging it. A critic output is used to tune the action generating NN weights so that the action generating NN approximates the gripper/environment dynamics accurately. The adaptive critic NN controller utilizes a conventional proportional and derivative (PD) tracking loop to enable the fingers to follow a desired trajectory and an additional force control loop to ensure that the predefined forces are applied on the object. Closed-loop performance is guaranteed through novel NN weight algorithms that are proposed in the paper.

In Section II, a brief background on NNs and stability of nonlinear system are presented. The dynamic modeling of a three-finger gripper used in our work is given in Section III along with a novel adaptive critic algorithm. Simulation results are included to illustrate the validity of the approach in Section IV. Section V presents the conclusions of this work.

II. NN Background

A general function $f(x) \in C^{(s)}$ can be approximated using an NN with at least two layers of appropriated weights given by

$$f(x) = W^T \sigma(V^T x) + \xi \qquad (2.1)$$

where W and V are constant-weight matrices of appropriate dimension (the first column of these matrices include the bias vectors so that tuning the weight matrices results in tuning the biases as well), x is the input vector, $\sigma(V^T x)$ is the vector of hidden-layer activation functions, and ξ is the error in approximation. If the input to the hidden-layer weight matrix V is selected as the identity matrix and the vector of hidden-layer activation functions is selected as a basis function, then a one-layer NN will result. Define the net output y for a one-layer NN as

$$y = W^T \varphi(x). \qquad (2.2)$$

For suitable approximation, $\varphi(x)$ must form a basis to the function that is being approximated. For instance, it is well known in the NN literature that radial basis functions form a basis [6] to a large class of functions. From the NN approximation theory, it is known that (2.2) can approximate any continuous function over a compact set and a set of target weights exist. The control objective is to tune the actual weight estimates such that they approach their targets. In this paper, we will show how to select basis functions using the physics of the gripper (dynamic variables) instead of selecting them in an arbitrary manner. Further, the tedium of solving analytically the regression matrix [6] needed for each gripper as required in the conventional adaptive control is avoided. Novel NN weight updates are also introduced.

All neurocontroller designs have relied upon the function approximation property (2.1). It would be desirable to use more advanced learning and intelligent features of NNs in controls design as suggested in [11]. A particular intriguing NN topology is adaptive critic. Adaptive critic designs [11] utilize reinforcement learning for NN weight tuning. These designs address the general problem of how to optimize a measure of utility or goal satisfaction over multiple time periods into the future, in an unknown noisy, and nonlinear environment.

In the adaptive critic NN architecture, the critic NN evaluates the system performance and tunes the action-generating NN, which in turn provides the control input signal to the system being controlled. Papers dealing with control using adaptive critic NN architecture are too numerous to mention. For details see [11]–[14]. Very few papers [13] present the closed-loop stability analysis with performance guarantee. This paper overcomes these limitations.

A. Stability of Systems

To formulate the controller, the following stability notion is needed. Consider the nonlinear system given by

$$\dot{x} = f_1(x, u)$$
$$y = h_1(x) \tag{2.3}$$

where t is the time, $x(t)$ is a state vector, $u(t)$ is the input vector, and $y(t)$ is the output vector [6]. The solution to (2.3) is *uniformly ultimately bounded* (UUB) if for any U, a compact subset of $\Re^n$, and all $x(t_o) = x_o U$ there exists an $\varepsilon > 0$ and a number $T(\varepsilon, x_O)$ such that $\|x(t)\| < \varepsilon$ for all $t \geq t_0 + T$. ∎

III. GRIPPER MODELING AND CONTROL DESIGN

The dynamics of a single finger of a three-finger gripper in the x-direction, as shown in Fig. 1, are expressed as [3]

$$m\ddot{x}_1 + \lambda_1 = \tau_1 + F_{C1} - \tau_{d1} \tag{3.1}$$

where x_1 is the position in the direction x, $\dot{x}_1$, $\ddot{x}_1$ the velocity and acceleration in the x-direction, respectively, m is the mass of a finger for all the moving parts, λ_1 represents the force required to grasp the objects, τ_{d_1} is a bounded unknown disturbance whose upper bound is given by $\|\tau_{d1}\| \leq d_M$, τ_1 is the control input, and F_{C1} the Coulomb frictional force of the actuator gear system. The friction can be accurately represented by the LuGre model [5] as given next. The finger dynamics in the x-direction in (3.1) are expressed using LuGre model as shown in (3.2) at the bottom of the page, where

$$g(\dot{x}_1) = \frac{fc_1 + (fs_1 - fc_1)e^{-(\dot{x}_1/v_{s1})^2}}{\sigma_{o1}} \tag{3.3}$$

and z_1 is incorporated as an additional state variable. According to [5], the additional state variable is not related to any physical variable. However, the LuGre model is an experimentally validated model for the friction and the contact dynamics.

The LuGre model in (3.2) captures the static and dynamic characteristics of friction. The static parameters include the viscous ($f_{v1} > 0$), Coulomb ($f_{c1} > 0$), and static ($f_{s1} > 0$). The dynamic parameters are represented by $\sigma_{o1} > 0$ and $\sigma_{11} > 0$ [5] with the Stribeck velocity factor denoted as $V_{s1} > 0$. The dynamics can be rewritten in a compact form as

$$\ddot{x}_1 = m^{-1}fe(\dot{x}_1, z_1) + m^{-1}(\tau_1 - \lambda_1 - \tau_{d1}) \tag{3.4}$$

with $fe(\dot{x}_1, z_1)$ as a nonlinear function (in terms of the states $\dot{x}$ and z) of the gripper dynamics and it is expressed as

$$fe(\dot{x}_1, z_1) = \left[\left(\sigma_{01} - \left(\frac{\sigma_{11}|\dot{x}_1|}{g(\dot{x}_1)}\right)\right)z_1 - (\sigma_{11} + fv_1)\dot{x}_1\right]. \tag{3.5}$$

The dynamics shown in (3.4) can be expanded to a gripper with three fingers, each finger moving on the x–y plane. The dynamics of the three-finger gripper can now be written as

$$\ddot{x} = M^{-1}fe(\dot{x}, z) + M^{-1}(\tau - \lambda - \tau_d) \tag{3.6}$$

where $x \in \Re^6$ is the positional vector composed of $(x_1, y_1, x_2, y_2, x_3, y_3)^T$, which represent the x and y coordinates of the fingers 1, 2, and 3, respectively, $M \in \Re^{6 \times 6}$ is the diagonal mass matrix, $fe(\dot{x}, z) \in \Re^6$ is a vector of nonlinear functions

$$fe(\dot{x}, z) = [fe(\dot{x}_1, z_1), fe(\dot{y}_1, z_2), fe(\dot{x}_2, z_3),$$
$$fe(\dot{y}_2, z_4), fe(\dot{x}_3, z_5), fe(\dot{y}_3, z_6)]^T$$

with $fe(\dot{x}_1, z_1), fe(\dot{y}_1, z_2) \ldots fe(\dot{y}_3, z_6)$ are the nonlinear functions of the dynamics in terms of the x and y coordinates of the finger, and its corresponding additional state z. Thus, the vector $fe(\dot{x}, z)$ is composed of the dynamics of all the fingers moving in the x–y plane. The mass matrix $M \in \Re^{6 \times 6}$ is expressed as

$$M = \begin{bmatrix} \frac{J_G}{\gamma^2+m} & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{J_G}{\gamma^2+m} & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{J_G}{\gamma^2+m} & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{J_G}{\gamma^2+m} & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{J_G}{\gamma^2+m} & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{J_G}{\gamma^2+m} \end{bmatrix} \tag{3.7a}$$

$$\frac{d}{dt}\begin{bmatrix} x_1 \\ \dot{x}_1 \\ z_1 \end{bmatrix} = \begin{bmatrix} \dot{x}_1 \\ m^{-1}\left[-\lambda_1 + \left(\sigma_{o1} - \sigma_{11}\frac{|\dot{x}_1|}{g(\dot{x}_1)}\right)z_1 - (\sigma_{11} + f_{v1})\dot{x}_1 + \tau_1 - \tau_{d1}\right] \\ -\frac{|\dot{x}_1|}{g(\dot{x}_1)}z_1 + \dot{x}_1 \end{bmatrix} \tag{3.2}$$
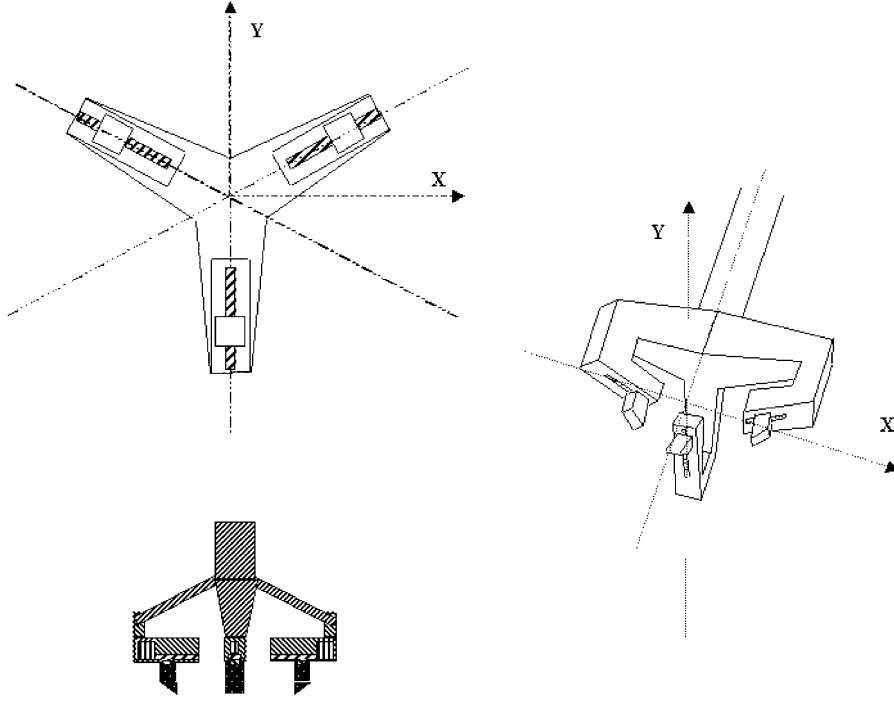
Fig. 1.   Schematic of a three-finger robot gripper.

with J_G known as the moment of inertia, m the mass of the moving parts for each finger (defined to be equal), and γ radius of the outer pinion, $\tau \in \Re^6$ is the control input vector, $\tau_d \in \Re^6$ the vector of bounded disturbances whose upper bound is $\|\tau_d\| \le d_M$, and $\lambda \in \Re^6$ is the vector of grasping forces. The vector of nonlinear functions $fe(\dot{x}, z)$ can be expressed as

$$fe(\dot{x}, z) = \begin{bmatrix} \left(\sigma_{01} - \left(\frac{\sigma_{11}|\dot{x}_1|}{g(\dot{x}_1)}\right)\right) z_1 - (\sigma_{11} + fv_1)\dot{x}_1 \\ \left(\sigma_{02} - \left(\frac{\sigma_{12}|\dot{y}_1|}{g(\dot{y}_1)}\right)\right) z_2 - (\sigma_{12} + fv_2)\dot{y}_1 \\ \left(\sigma_{03} - \left(\frac{\sigma_{13}|\dot{x}_2|}{g(\dot{x}_2)}\right)\right) z_3 - (\sigma_{13} + fv_3)\dot{x}_2 \\ \left(\sigma_{04} - \left(\frac{\sigma_{14}|\dot{y}_2|}{g(\dot{y}_2)}\right)\right) z_4 - (\sigma_{14} + fv_4)\dot{y}_2 \\ \left(\sigma_{05} - \left(\frac{\sigma_{15}|\dot{x}_3|}{g(\dot{x}_3)}\right)\right) z_5 - (\sigma_{15} + fv_5)\dot{x}_3 \\ \left(\sigma_{06} - \left(\frac{\sigma_{16}|\dot{y}_3|}{g(\dot{y}_3)}\right)\right) z_6 - (\sigma_{16} + fv_6)\dot{y}_3 \end{bmatrix}$$
(3.7b)

where

$$g(\dot{p}) = \frac{fc_i + (fs_i - fc_i)e^{-(p/v_{si})^2}}{\sigma_{oi}}$$
(3.7c)

with the variable p taking values from $p = x_1, y_1, x_2, y_2, x_3, y_3$, and $\sigma_{0i}, \sigma_{1i}, fv_i, fc_i, fs_i;\ i = 1, \ldots, 6$, are the static and dynamic parameters, z_i is the additional state, v_{si} is the Stribeck factor, respectively, for each finger in the x and y directions.

A. Gripper Controller Design

Our objective is to design a control input $\tau \in \Re^6$ that guarantees a desired gripper motion and applied force. Given a desired trajectory $x_d \in \Re^6$ for the fingers, define the filtered tracking error $r \in \Re^6$ as

$$r = \dot{e} + \Delta e$$
(3.8)

where $\Delta \in \Re^{6\times 6}$ is a design matrix selected through pole placement with $e \in \Re^6$, $\dot{e} \in \Re^6$ representing the trajectory error in position $e = x - x_d$, and velocity $\dot{e} = \dot{x} - \dot{x}_d$, respectively. This selection must ensure that when the filtered tracking error converges to zero, the trajectory error $e(t)$ eventually converges to zero. Common usage is to select Δ diagonal with positive entries. Then (3.8) is a stable system so that $e(t)$ is bounded as long as the controller guarantees that the filtered tracking error $r(t)$ is bounded.

In the presence of bounded disturbances, the gripper dynamics are expressed from (3.6) as

$$M\ddot{x} - fe(\dot{x}, z) + \lambda + \tau_d = \tau.$$
(3.9)

Differentiating (3.8) and multiplying by the inertia matrix M, one obtains

$$M\dot{r} = M\ddot{x} - M\ddot{x}_d + M\Delta\dot{e}.$$
(3.10)

Rewriting (3.10) using (3.9) as

$$M\dot{r} = fe(\dot{x}, z) + \tau - \lambda - \tau_d - M\ddot{x}_d + M\Delta\dot{e}$$
(3.11)

where

$$\dot{x} = \dot{x}_d - \Delta e + r.$$
(3.12)

Defining the unknown nonlinear dynamics of the gripper as

$$f(h) = fe(\dot{x}, z) - M\ddot{x}_d + M\Delta\dot{e}$$
(3.13)

yields the filtered tracking error system

$$M\dot{r} = f(h) + \tau - \tau_d - \lambda$$
(3.14)

where $\lambda \in \Re^6$ represents the actual force.

Given a smooth trajectory and when the mass matrix M is accurately known, the control input can be selected as

$$\tau = (-f(h) - K_v r) + (\lambda_d + K_f \lambda_e) \qquad (3.15)$$

with $f(h) \in \Re^6$ known accurately, where $h \in \Re^{24} = [\dot{x}, \ddot{x}_d, \dot{e}, z]^T$, and $K_v \in \Re^{6 \times 6}$ is the gain matrix. The outer loop $\lambda_d + k_f \lambda_e$ is a proportional force controller where $K_f \in \Re^{6 \times 6}$ is the gain matrix for the force controller component, $\lambda_d \in \Re^6$ represents the desired force vector, and $\lambda_e \in \Re^6$ is the force error $\lambda_e = \lambda_d - \lambda$. Applying (3.15) in (3.14) in the absence of disturbances, the filtered tracking error system can be shown to be asymptotically stable. However, the viscous and the Coulomb frictional forces are not known and nonmeasurable and hence the function $f(h)$ in (3.14) is unknown. Consequently, a novel learning controller scheme is necessary. In this paper, the gripper dynamics and the object contact environment are considered unknown and a one-layer NN-based critic is employed to approximate the contact dynamics that is given by $f(h)$. Further, by appropriately choosing the NN weight updates, the stability of the closed-loop system is proven in the subsequent sections.

Let the control input be selected as

$$\tau = -\hat{f}(h) - K_v r + v(t) + (\lambda_d + K_f \lambda_e) \qquad (3.16)$$

with $v(t) \in \Re^6$ being an auxiliary input, then the closed-loop system dynamics become

$$M\dot{r} = f(h) - \hat{f}(h) - K_v r + v(t) + (\lambda_d + K_f \lambda_e) - \tau_d - \lambda \quad (3.17)$$

or

$$M\dot{r} = \tilde{f}(h) - K_v r + v(t) + (\lambda_e + K_f \lambda_e) - \tau_d \qquad (3.18)$$

where $\hat{f}(h) \in \Re^6$ is the approximated value of $f(h) \in \Re^6$, and $\tilde{f}(h) \in \Re^6$ is the approximation error $\tilde{f}(h) = f(h) - \hat{f}(h)$. The designer beforehand specifies the approximation error bound using position and force tolerance values. From (3.18), it is clear that the closed-loop filtered tracking error system is driven by the functional approximation error. If the functional approximation error and disturbances are nonzero, then the stability of the closed-loop filtered tracking error system needs to be ensured.

B. Adaptive Critic NN Controller Design

Here, a one-layer action generating NN is used to approximate the unknown dynamics. The unknown dynamics are expressed as linear in the tunable NN weights as given in (3.19). Along with a novel tunable algorithm, a secondary adaptive function (known as a critic signal) is developed by the Lyapunov stability analysis [2]. Assume, therefore, that there exists a constant ideal set of weights $W \in \Re^{24 \times 6}$ for a one-layer NN, where $h \in \Re^{24}$ represents the input so that the nonlinear dynamics can be written as [6]

$$f(h) = W^T \phi(h) + \xi \qquad (3.19)$$

where $\phi(h) \in \Re^{24}$ provides a suitable basis and the error in approximation $\xi \in \Re^6$ such that $\|\xi\| \leq \xi_N$ with the bound ξ_N known (e.g., maximum position and force tolerances). For suitable approximation properties, it is necessary to select a large

enough number of hidden-layer neurons. However, through inspection, an NN input vector can be chosen based on the function $f(h)$ it is trying to build [6]. One such basis vector is given by $h = [\dot{x}, \ddot{x}, \dot{e}, z]^T$. Next, the adaptive critic controller structure is defined.

C. Adaptive Critic Controller Structure

A choice of the critic output signal is given by

$$R = P\sigma(r) + \rho \qquad (3.20)$$

where $P \in \Re^{6 \times 6}$ is a diagonal positive-definite matrix, $\sigma(r) \in \Re^6$ is the vector of sigmoid functions, and $\rho \in \Re^6$ is an auxiliary critic signal which is defined later. Defining the action-generating NN functional estimate by

$$\hat{f}(h) = \hat{W}^T \phi(h) \qquad (3.21)$$

where $\hat{W} \in \Re^{24 \times 6}$ is a matrix of actual weights. The next step is to determine the weight updates so the performance of the closed-loop filtered tracking error dynamics of the fingers is guaranteed.

Let W be a matrix of unknown target weights required for the approximation to hold in (2.2) and assume they are bounded by known values so that

$$\|W\| \leq W_{max} \qquad (3.22)$$

then the error in weights $\tilde{W} \in \Re^{24 \times 6}$ during estimation is defined as

$$\tilde{W} = W - \hat{W}. \qquad (3.23)$$

Let the control input be selected as

$$\tau = -\hat{W}^T \phi(h) - K_v r + v(t) + (\lambda_d + K_f \lambda_e). \qquad (3.24)$$

Substituting the control input (3.24) in (3.14) yields the filtered tracking error system as

$$M\dot{r} = -K_v r + \tilde{W}^T \phi(h) + v(t) + \xi - \tau_d + (\lambda_e + K_f \lambda_e). \qquad (3.25)$$

The structure of the proposed adaptive critic NN controller is shown in Fig. 2. An inner action-generating NN loop eliminates the nonlinear dynamics of the fingers. The outer PD tracking loop designed via Lyapunov analysis guarantees the object contact control stability and accuracy in following a desired planned trajectory. The outer proportional force controller loop ensures that the fingers exert the desired forces. Finally, the proposed adaptive NN critic design is modular so that existing industrial controllers can be easily modified to obtain the proposed one by simply adding the inner NN and robust control loops. This modular design avoids the need for the redesign of the industrial control systems.

The next step is to determine an appropriate weight tuning method so that the closed-loop stability of the grasping controller can be demonstrated.

Theorem 3.1: Assume that the desired trajectory for the fingers, the unknown disturbances, and the approximation errors are bounded, respectively, by the constants x_B, d_B, ξ_N. Select the action-generating NN weight tuning update as

$$\dot{\hat{W}} = \Gamma \phi(h)(r + \sigma'(\bar{h})^T M^{-1} P^T R)^T - \Gamma \hat{W} \qquad (3.26)$$
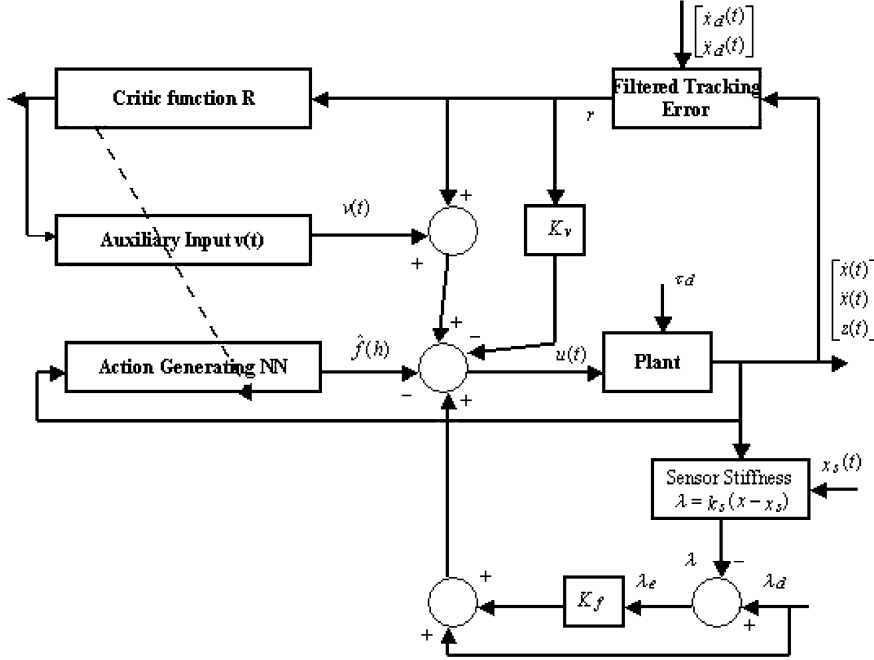
Fig. 2.   Adaptive critic NN controller structure.

where $\Gamma \in \Re^{24\times24}$ is a constant learning rate matrix and with $K_{v_{\min}}$ the minimum singular value of the gain matrix K_v, satisfying

$$K_{v_{\min}} > \frac{1}{2}W_{\max}^2. \tag{3.27}$$

Define the robust input (auxiliary input) as

$$v = -K\frac{M^{-1}\sigma'(\bar{h})PR+r}{\|M^{-1}\sigma'(\bar{h})PR+r\|} \tag{3.28}$$

with the auxiliary critic signal selected as

$$\dot{\rho} = -P\sigma'(\bar{h})M^{-1}K_vr \tag{3.29}$$

where $\sigma'(\bar{h}) \in \Re^{6\times6}$ is the diagonal matrix derivative of $\sigma(\bar{h}) \in \Re^6$, $P \in \Re^{6\times6}$ is a constant positive-definite diagonal matrix, and $\sigma(\bar{h})$ a sigmoid term where $\bar{h} = Bh$ with $\bar{h} \in \Re^6$, $B \in \Re^{6\times24}$ is a constant design matrix upper bounded as $\|B\| \leq \Psi$, and $K \geq (\xi_N + d_B)$. Then the tracking error $r(t)$ and the weight estimation errors $\tilde{W}$ are UUB. Further, the force errors are also UUB.

Proof: In the presence of disturbances and approximation errors, and not taking into consideration initially the force control loop, the closed-loop system is expressed as

$$M\dot{r} = -K_vr + \tilde{W}^T\phi(h) + v(t) + \xi - \tau_d. \tag{3.30}$$

a) Position error and NN weights estimation error bounds:
Select the Lyapunov function candidate $V \in \Re$ as

$$V = \frac{1}{2}\alpha^T\bar{M}\alpha + \frac{1}{2}\text{tr}\left\{\tilde{W}^T\Gamma^{-1}\tilde{W}\right\} \tag{3.31}$$

where $\alpha \in \Re^{12}$ and $\bar{M} \in \Re^{12\times12}$ are given by

$$\alpha = [r \;\; R]^T, \qquad \bar{M} = \begin{bmatrix} M & 0 \\ 0 & I \end{bmatrix}.$$

Recall the critic signal

$$R = P\sigma(r) + \rho \tag{3.32}$$

whose time derivative is defined as

$$\dot{R} = P\sigma'(r)\dot{r} + \dot{\rho}. \tag{3.33}$$

We evaluate the first derivative of V along the system trajectories to get

$$\dot{V} = r^TM\dot{r} + R^T\dot{R} + \text{tr}\left\{\tilde{W}^T\Gamma^{-1}\dot{\tilde{W}}\right\} + \frac{1}{2}r^T\dot{M}r. \tag{3.34}$$

Since the mass matrix M is a constant matrix of mass elements of the fingers, the fourth term in (3.34) becomes zero. Substituting (3.30) in (3.34), we have

$$\dot{V} = r^T(-K_vr) + r^T\tilde{W}^T\phi(h) + r^T(\varepsilon + \tau_d + v) \\ + R^TP\sigma'\dot{r} + R^T\dot{\rho} + \text{tr}\left\{\tilde{W}^T\Gamma^{-1}\dot{\tilde{W}}\right\}. \tag{3.35}$$

Since the mass matrix is a diagonal positive-definite matrix, the tracking error can be expressed as

$$\dot{r} = -M^{-1}K_vr + M^{-1}\tilde{W}^T\phi(h) + M^{-1}(\varepsilon + \tau_d + v). \tag{3.36}$$

Substituting (3.36) into (3.35)

$$\dot{V} = -r^TK_vr + r^T\tilde{W}^T\phi(h) + r^T(\varepsilon + \tau_d + v) + R^TP\sigma' \\ \times \left[-M^{-1}K_vr + M^{-1}\tilde{W}^T\phi(h) + M^{-1}(\varepsilon + \tau_d + v)\right] \\ + R^T\dot{\rho} + \text{tr}\left\{\tilde{W}^T\Gamma^{-1}\dot{\tilde{W}}\right\}. \tag{3.37}$$

Rewrite (3.37) as

$$\dot{V} = -r^TK_vr \\ + \text{tr}\left\{\tilde{W}^T\left[\phi(h)r^T + \Gamma^{-1}\dot{\tilde{W}} + P\phi(h)M^{-1}\sigma'R^T\right]\right. \\ + \left[M^{-1}\sigma(\bar{h})PR + v\right]^T(\varepsilon + \tau_d + v) \\ \left. + R^T\left[P\sigma'M^{-1}K_vr + \dot{\rho}\right]\right\}. \tag{3.38}$$

Since $\tilde{W} = W - \hat{W}$ and $\dot{\tilde{W}} = \dot{W} - \dot{\hat{W}}$, then $\dot{\tilde{W}} = -\dot{\hat{W}}$. Substituting the weight update for the action-generating NN from (3.26), the critic signal (3.29), and robust control term (3.28) into (3.38), the first derivative of the Lyapunov function can be expressed as

$$\dot{V} = -r^T K_v r + \text{tr}\left\{\tilde{W}^T \dot{\hat{W}}\right\}. \tag{3.39}$$

Rewriting (3.39) as

$$\dot{V} = -r^T K_v r + \text{tr}\left\{\tilde{W}^T (W - \tilde{W})\right\} \tag{3.40}$$

which is negative as long as the term in the braces is negative. Rearranging (3.40) results in

$$\dot{V} = -r^T K_v r + \text{tr}\left\{\tilde{W}^T W - \tilde{W}^T \tilde{W} - \frac{1}{4} W^T W\right\}$$
$$+ \frac{1}{4}\text{tr}\{W^T W\}. \tag{3.41}$$

In other words

$$\dot{V} \le -K_{v \min} \|r\|^2 - \left(\left\|\tilde{W}\right\| - \frac{W_{\max}}{2}\right)^2 + \frac{1}{4}W_{\max}^2 \tag{3.42}$$

yields the first derivative negative as long as

$$\|r\| > \frac{W_{\max}}{2\sqrt{K_{v \min}}} \tag{3.43}$$

or

$$\left\|\tilde{W}\right\| > W_{\max}. \tag{3.44}$$

From (3.43) and (3.44), $\dot{V}$ is negative outside a compact set. According to a standard Lyapunov theorem [6], it can be concluded that the tracking error $r(t)$ and the NN weights estimates $\tilde{W}$ are UUB.

b) *Force error bounds:*

To show the bound on the force tracking error λ_e, we use an approach that can be compared to Barbalat's extension [6]. Thus, note first that in part of the proof we have shown that all quantities on the right-hand side of (3.36) are bounded. Therefore, from the invertibility of M it follows that $\dot{r}$ is bounded. Now, substitute the control (3.24) into the error dynamics (3.14) to obtain

$$M\dot{r} = -K_v r + \tilde{W}^T \phi(h) + v(t) + \xi - \tau_d + (\lambda_e + K_f \lambda_e) \tag{3.45}$$

or

$$M\dot{r} = -K_v r + \tilde{W}^T \phi(h) + v(t) + \xi - \tau_d + \lambda_e + K_f \lambda_e. \tag{3.46}$$

This may be written as

$$(1 + K_f)\lambda_e = M\dot{r} + K_v r - \tilde{W}^T \phi(h) - v(t) - \xi + \tau_d$$
$$\equiv B(\dot{r}, x, \tilde{W}, \tau_d, \xi) \tag{3.47}$$

where all quantities are the right-hand side are bounded. Therefore, we get

$$\lambda_e = (1 + K_f)^{-1} B(\dot{r}, x, \tilde{W}, \tau_d, \xi). \tag{3.48}$$

This expression shows that the force tracking error λ_e is bounded. ∎

Remark 1: Equations (3.43) and (3.48) present the filtered tracking error and weight estimation error bounds, respectively. The tracking error bound can be made as small as desired by increasing the smallest eigenvalue $K_{v \min}$.

Remark 2: The force tracking error bound (3.48) can be made as small as desired by increasing the force tracking error gain K_f. Increasing the force tracking error gain may cause overshoots and undershoots, which, in turn, may damage the object that is being grasped.

The contribution of both the NN and the robust control terms can be evaluated by removing the adaptive critic NN inner loop and the robust control term from the controller design. Then a hybrid PD position with a proportional force controller will result as presented next.

If the NN and the robust inputs are ignored, the control input becomes

$$\tau = -K_v r + (\lambda_d + K_f \lambda_e). \tag{3.49}$$

Substituting the control input (3.49) in (3.14) yields the filtered tracking error system as

$$M\dot{r} = -K_v r + f(h) - \tau_d + (\lambda_e + K_f \lambda_e) \tag{3.50}$$

where the nonlinear gripper and the contact dynamics are assumed to be bounded above by a constant given by $\|f(h)\| \le f_M$. Closely observing the torque input from (3.49), it is clear that the controller is a hybrid PD position and a proportional force controller. Of course, a proportional, integral, and derivative (PID) controller can be designed for both position and force components and similar analysis can be carried out. However, in any case, an NN inner loop is still required for achieving the best performance during a grasping operation. The performance of the hybrid PD/proportional force controller is presented next when the NN inner loop is removed.

Theorem 3.2: Assume that the desired trajectory of the fingers and the unknown disturbances and bounded, respectively, by the constants x_B and d_B. Select the control input for the gripper from (3.49), and then the position and force tracking errors are UUB.

Proof: In the presence of disturbances and dynamics, and not taking into consideration initially the force control loop, the closed-loop system (3.50) is expressed as

$$M\dot{r} = -K_v r + f(h) - \tau_d. \tag{3.51}$$

a) *Position error bound:*

Select the Lyapunov function candidate $V \in \Re$ as

$$V = \frac{1}{2}r^T M r \tag{3.52}$$

whose first difference is given by

$$\dot{V} = r^T M \dot{r} + \frac{1}{2}r^T \dot{M} r. \tag{3.53}$$

Since the mass matrix M is a matrix of constant elements, the second term in (3.53) becomes zero. Substituting (3.51) in (3.53) yields

$$\dot{V} = r^T(-K_v r + f(h) - \tau_d). \tag{3.54}$$

Equation (3.54) can be expressed as

$$\dot{V} \le -\|r\| \left(K_{v\min} \|r\| - (f_M + d_M) \right). \tag{3.55}$$

The Lyapunov derivative $\dot{V} \le 0$ is negative if and only if

$$\|r\| > \frac{(f_M + d_M)}{K_{v\min}}. \tag{3.56}$$

According to a Lyapunov theorem [6], it can be concluded that the tracking error $r(t)$ is UUB.

b) Force error bound:

To show an upper bound on the force tracking error λ_e, we use an approach similar to that in Theorem 3.1. Thus, note first that in part of the proof we have shown that all quantities on the right-hand side of (3.51) are bounded given the unknown gripper and contact dynamics are bounded above. Therefore, from the invertibility of M it follows that $\dot{r}$ is bounded. Rewriting (3.50) as

$$(1 + K_f)\lambda_e = M\dot{r} + K_v r - f(h) + \tau_d \equiv B_1(\dot{r}, x, f_M, \tau_d) \tag{3.57}$$

where all quantities are the right-hand side are bounded. Therefore, we get

$$\lambda_e = (1 + K_f)^{-1} B_1(\dot{r}, x, f_M, \tau_d). \tag{3.58}$$

This expression shows that the force tracking error λ_e is bounded and can be made as small as desired by increasing the force tracking error gain K_f. ∎

Remark 1: This theorem clearly demonstrates that when the NN loop is ignored, a hybrid PD position and proportional force controller results. A similar analysis can be done even if a hybrid PID position and force controller are used. The expressions for the tracking and force error bounds will be similar to (3.56) and (3.58), respectively, due to the presence of uncertainties in the dynamics and external disturbances.

Remark 2: Equations (3.56) and (3.58) present the tracking error bound on the position and force, respectively. These tracking and force error bounds depend upon the upper bound on the unknown dynamics of the gripper, contact, and the controller gains. Though the error bounds can be reduced arbitrarily by selecting the gains, the resulting error bounds will be larger than in the case when an adaptive critic NN controller is not utilized. The NNs learn the uncertain dynamics so that the tracking error bounds depend upon the approximation error ξ_N, which is considerably smaller than the bound on the uncertain dynamics f_M.

Remark 3: The PD or PID controller gain tuning can be avoided with the addition of an NN inner loop.

IV. SIMULATION RESULTS

In this section, the adaptive critic NN controller is simulated and the control objective is to guide the fingers of a robot gripper to follow a trajectory. The dynamics of the gripper are expressed as (3.36), with $J_G = 6.1 \times 10^{-6}$ kg·m^2 the moment of inertia,

$m = 0.10$ kg is the mass component for the x and y direction of the moving parts of each finger, and $\gamma = 0.294{*}10^{-3}$ N/m is the radius of the outer pinion. The LuGre model for the Coulomb friction, which is obtained from [5], is used in the simulation. The additional state variables defined in the LuGre model are initialized to zero.

The static and dynamics parameters of the LuGre model are selected as $\sigma_{oi} = 0.1$, $\sigma_{1i} = 0.2$, $f_{vi} = 2.1 \times 10^{-3}$, $f_{ci} = 0.17$, $f_{si} = 0.02$, $v_{si} = 0.08; i = 1, \dots, 6$ for the three fingers in both x and y directions. The force measuring method described in [3] is used. Select (x_s, y_s) as the contact point of a finger on the object and (x, y) is the actual coordinate of a finger. The measured forces are calculated using the sensor stiffness coefficient $k_s = 3 \times 10^2$ N/m along with the deformation of the object in the x and y directions for a finger as $(x - x_s)$ and $(y - y_s)$, respectively. Then the sensed forces for each finger are given by $\lambda = k_s(x - x_s)$ if $(x > x_s)$ and $\lambda = k_s(y - y_s)$ if $(y > y_s)$, respectively, in the x and y directions. When $(x = x_s)$ and $(y = y_s)$, the finger has made contact with the object. When $(x < x_s)$ and $(y < y_s)$, the finger has not yet made any contact. Unless the contact with the object is made, necessary forces cannot be applied on the object. The sensed forces now given for the three fingers and separately expressed in the x and y components, are provided in the vector form as

$$\lambda = k_s[(x_1 - x_{s1}), (y_1 - y_{s1}), (x_2 - x_{s2}), \\ (y_2 - y_{s2}), (x_3 - x_{s3}), (y_3 - y_{s3})]^T.$$

For simulation purposes, a straight-line trajectory was planned for the fingers of the gripper along the x–y plane. The duration of travel on the path is expected to be 10 s. Any trajectory for the fingers can be planned as long as the fingers can travel along the path. The objective for the fingers is to enclose an object by traveling at a constant speed from their initial location by following the predefined path until the fingers have made contact with the object. Once the contact is established, the fingers have to exert the desired forces on the object for manipulation while ensuring that the trajectory tracking errors, any overshoots, and undershoots in the finger trajectory are minimized to avoid any potential damage to the object.

The adaptive critic NN-based controller allows the fingers not only to track the path and to make contact with the object at the right location but also it guides the fingers to apply the required forces once a contact is made even when the properties of the object and contact dynamics are not available. The adaptive critic NN controller uses an estimated value of the object and contact dynamics.

The system parameters given above were used to test the controller. Since the proposed adaptive NN controller has a conventional PD tracking loop, for critical damping, the positional and derivative gains of the PD tracking controller are selected using $K_v = 2\sqrt{K_p}$ and $\Lambda = K_p K_v^{-1}$. Using this relationship, the PD gain values were obtained as $K_p = 100I$, $K_v = 20I$, and $\Lambda = 5.I$ where I is the identity matrix of appropriate dimension. The proportional gain coefficient for the force controller is selected as $K_f = 64I$.
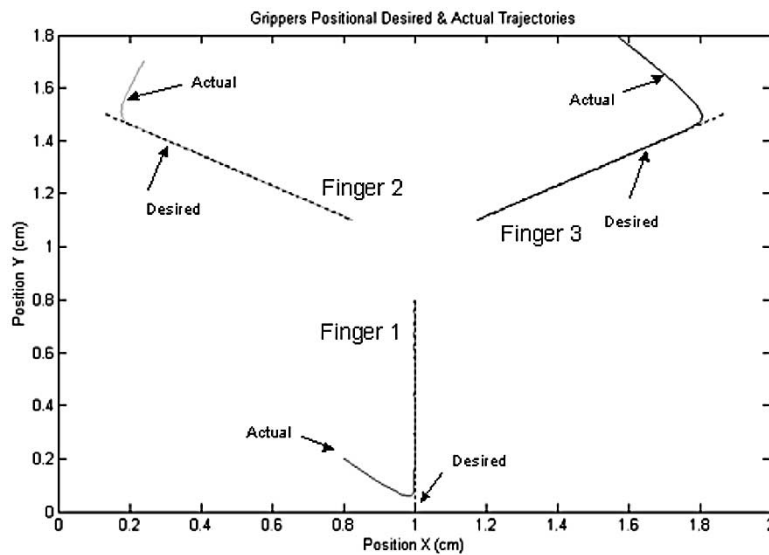
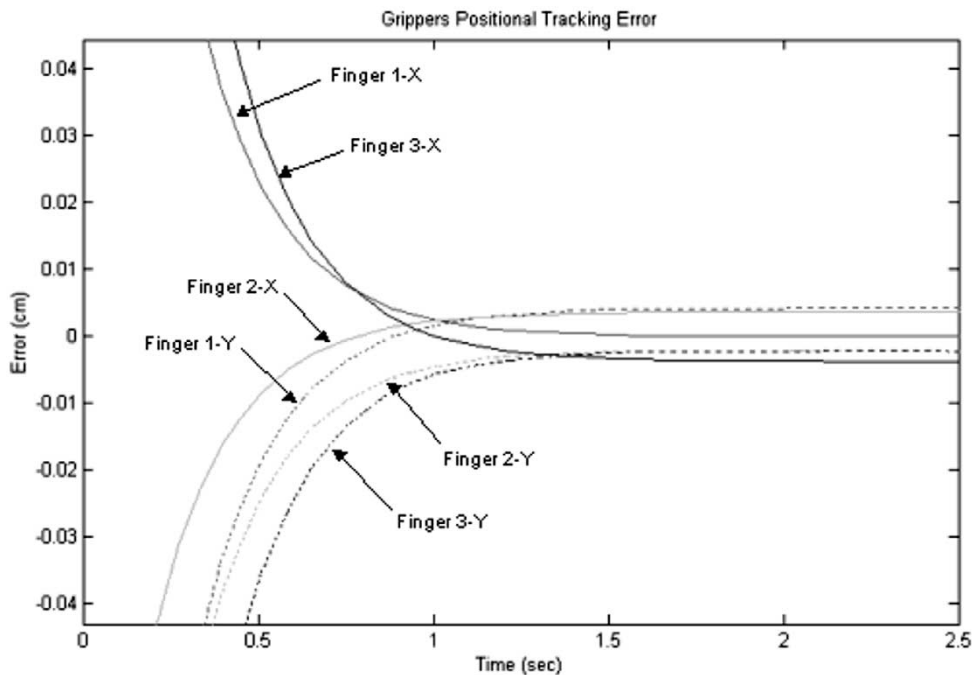Fig. 3. Tracking performance of the adaptive critic NN controller.

Fig. 4. Tracking error using the adaptive critic NN object contact controller.

Two cases were considered; 1) object contact and 2) grasping control. For both Case 1 and 2, the design parameters were held constant once they were selected. Note that the adaptive critic NN controller includes an NN inner loop, a PD position tracking controller outer loop, and an additional proportional force controller outer loop.

Case 1: Object Contact Control: In this case, the force controller loop is not required throughout the object contact control simulation. The objective of the fingers for object contact control is to reach and to make contact with the object. The NN controller loop directs the fingers toward the object for making contact. Figs. 3 and 4 depict the performance of the adaptive NN critic controller. Fig. 3 shows the actual and desired trajec-

tory response of the fingers along the x–y plane. Fig. 4 illustrates the corresponding trajectory tracking errors. It is clear that the fingers track the desired trajectories accurately with a small tracking error. Within a very short time of 1 s, the tracking errors converge close to zero.

Further, all the fingers stop once contact is established with the object so that no damage is induced. The performance of the adaptive critic NN controller can be best described as follows. Controller uncertainty with regards to gripper and contact dynamics will result in tracking errors. The critic NN generates an output signal based on the magnitude of the tracking error. The critic NN signal is used to tune the action-generating NN weights online so that the action-generating NN approximates
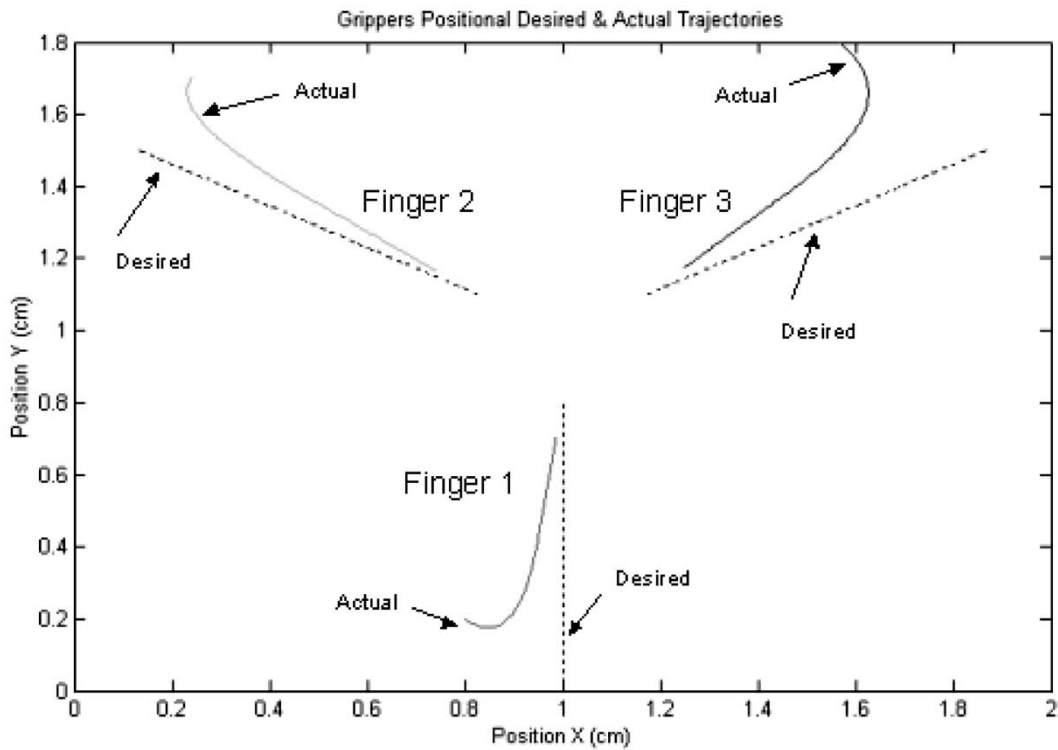
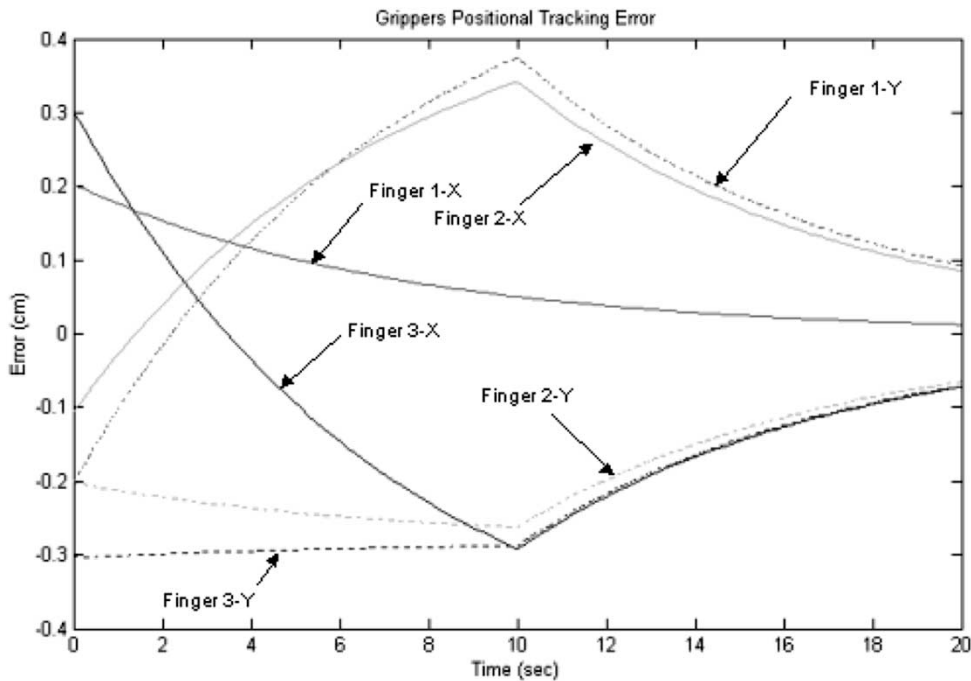Fig. 5.   Tracking response without the NN (PD object contact controller).

Fig. 6.   Tracking errors using PD object contact controller.

the uncertain contact and gripper dynamics accurately. As a consequence, the tracking error is significantly reduced and the fingers are able to follow the path and make contact with the object.

To show the contribution of the NN, the controller is simulated without the action generating and critic NNs. A conventional PD position controller results. Figs. 5 and 6 present the trajectory response and the tracking error, respectively. It is clear

that the fingers do not track the given trajectory. Further, the fingers do not even make contact with the object, as observed from the results. Thus, a standard PD controller without an NN is not suitable for object manipulation. From the analytical result presented in Theorem 3.2, it is clear that the tracking error is a function of the bound on the uncertain dynamics. Since there is no online learning via approximation, bounded errors render an inferior performance.
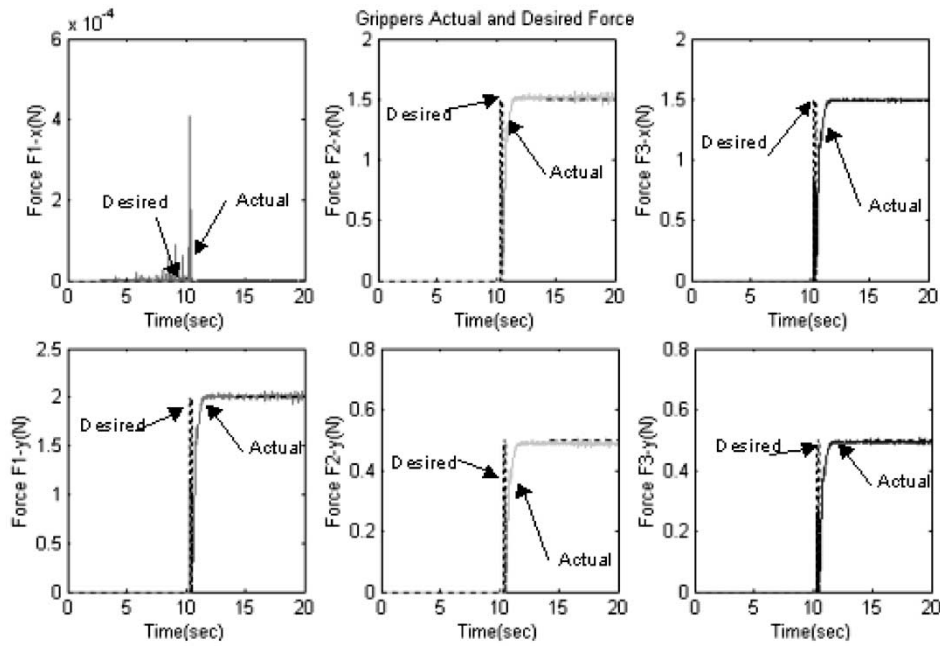
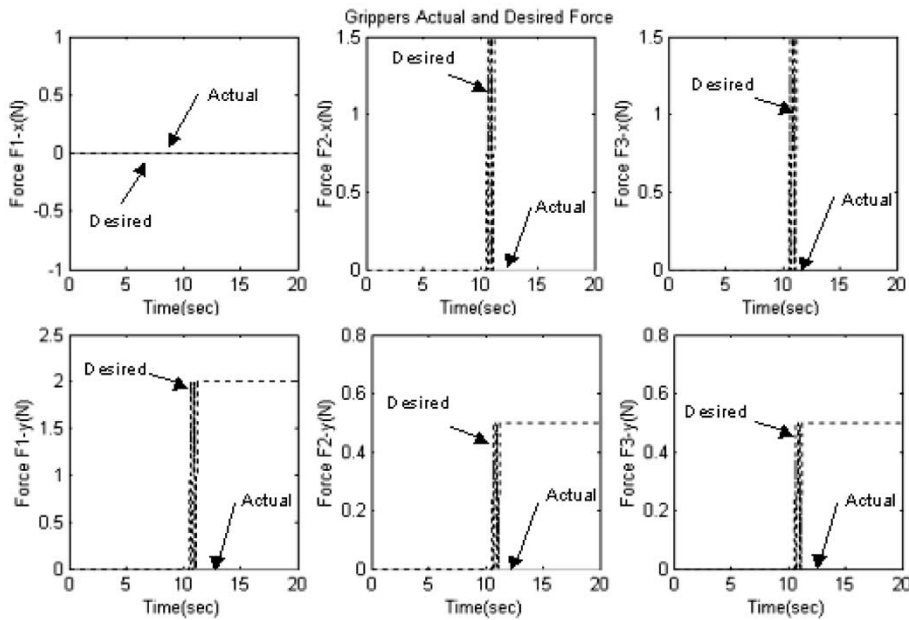Fig. 7. Force response using an adaptive critic NN grasping controller.

Fig. 8. Force response without the adaptive NN critic.

Case 2: Object Grasping Control: Here, the force-control loop is included and desired force values are selected by using the properties of the object to be secured. Also in this case, the contribution of the adaptive critic NN is demonstrated by removing the NN inner loop. Fig. 7 displays the performance of the NN-based adaptive critic hybrid position/force controller for the object that was used in Case 1. Similar to the case of object contact control, the tracking errors were very small. This figure presents the force response along with the desired forces for each finger in the x and y directions. From this figure, it is clear that the actual force tends to be equal to the desired force even when the gripper and the contact dynamics are unknown

to the controller. The fingers apply the prescribed forces once contact is established with the object. As a result, the proposed hybrid position/force controller performed impressively by successfully establishing contact with the object and then manipulating the object.

In order to study the contribution of the NN, the adaptive critic NN inner loop is removed for this simulation. Then the controller presented in Fig. 2 becomes a hybrid PD tracking controller for position with a proportional force control loop. Figs. 8 and 9 illustrate the response of the hybrid PD position/proportional force controller for the grasping task. Here the fingers do not make contact with the object. Consequently, the force re-
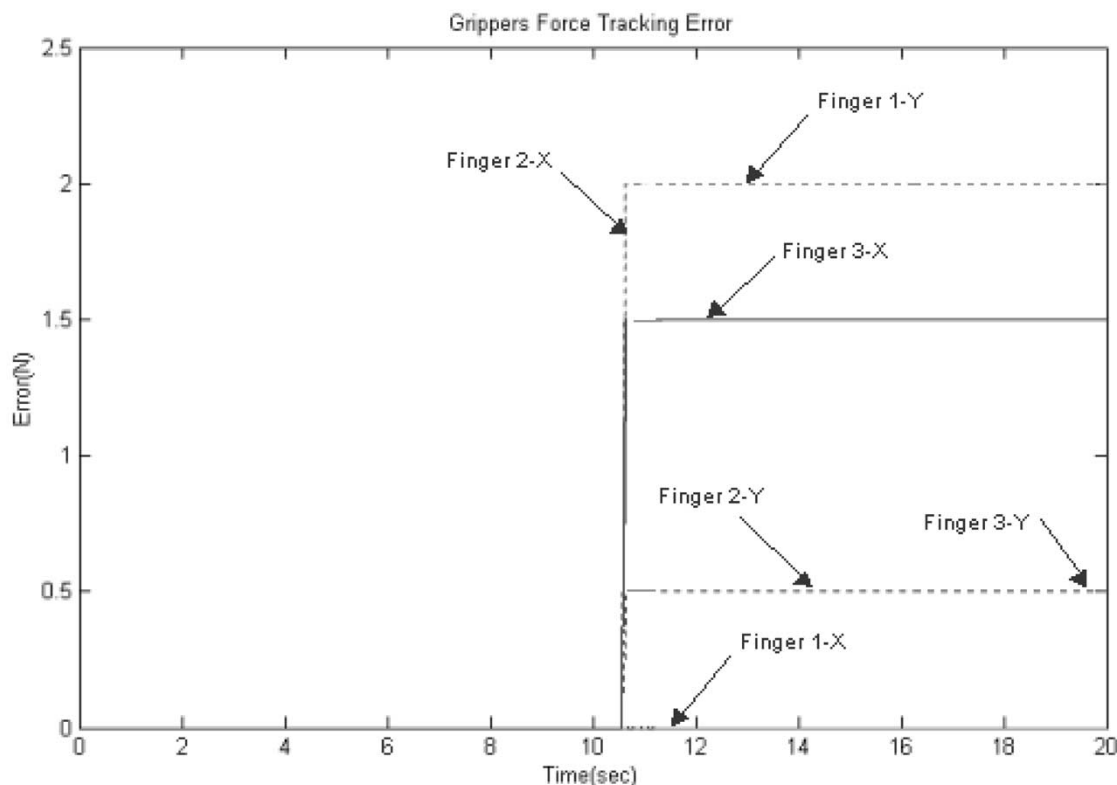
Fig. 9.   Force tracking errors without the adaptive NN critic.

sponse is zero, which makes the force tracking error magnitude equal to the desired force. As a result, the object is not manipulated, which is undesirable.

V. Conclusion

The task of grasping—object contact and manipulation—is complex and requires a sophisticated controller to compensate for the nonlinear gripper and contact dynamics. In this paper, a novel adaptive critic-based NN controller is presented for guiding the fingers so that they follow a predefined trajectory. The gripper controller includes an action-generating NN for compensating the dynamics, a critic signal for tuning the action generating NN, an outer PD position tracking loop, and an additional outer proportional force control loop. The tuning for the action-generating NN is performed online and it offers guaranteed tracking performance. The grasping task is accomplished when the gripper makes contact with the object and it secures the object via applying suitable forces. The net result is a novel hybrid position/force controller that guarantees the performance in terms of tracking a predefined path and then applying the prescribed forces on the object. The simulation results indicate that the proposed controller performs impressively compared to a hybrid PD position and a proportional force controller without the NN inner loop.

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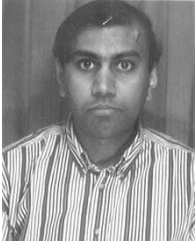
S. Jagannathan was born in Madurai, India. He received the Bachelor's degree in electrical engineering from College of Engineering, Guindy at Anna University, Madras, India, in 1986, the Master of Science degree in electrical engineering from the University of Saskatchewan, Saskatoon, SK, Canada, in 1989, and the Ph.D. degree in electrical engineering from the University of Texas at Austin, in 1994.

During 1986 to 1987, he was a Junior Engineer at Engineers India Limited, New Delhi, as a Research Associate and Instructor from 1990 to 1991, at the University of Manitoba, Winnipeg, MB, Canada, and worked at Systems and Controls Research Division, Caterpillar Inc., Peoria, IL, as a Consultant during 1994–1998. From 1998 to 2001, he was at the University of Texas at San Antonio (UTSA), and since September 2001, he has been at the University of Missouri-Rolla where the is currently an Associate Professor. He has coauthored more than 100 refereed conference and journal articles and several book chapters and one textbook entitled *Neural Network Control of Robot Manipulators and Nonlinear Systems* (London, U.K.: Taylor & Francis, 1999) with additional books being published on *Adaptive Discrete-Time Control* and *Quality of Service Control in Wireless and Computer Networks* (New York: Marcel Dekker). His research interests include adaptive control, MEMS-based sensor networks, computer/communication networks, prognostics, and autonomous systems/robotics. He currently holds 17 patents and several are pending.

Dr. Jagannathan received several gold medals and scholarships during his Bachelor's degree program and in high school. He was the recipient of the Presidential Award for Research Excellence at UTSA in 2001, the NSF CAREER award in 2000, Faculty Research Award in 2000, Patent Award in 1996, Sigma Xi "Doctoral Research Award" in 1994. He is a Member of Tau Beta Pi, Eta Kappa Nu, and Sigma Xi.

Gustavo Galan received the B.S. degree in electrical engineering from a university in Mexico, and the M.S. degree in electrical and computer engineering from the University of Texas, San Antonio, TX, in 2001. From 1999 to 2001, he worked on the control of underwater vehicles using neural networks and the control of autonomous robots for MARS greenhouse operation, a project funded by the Texas Space Grant Consortium and NASA. He is currently working in the software industry. He is the author of several published articles. His areas of interest include neural network control, embedded systems, and real-time control.