# Stable Adaptive Neural Control for a Nonlinear Robot System in the Presence of Actuator Failures and Uncertainties


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## Abstract

The bounded nonlinear time-varying actuator torque coefficients as well as uncertainties may deteriorate the performance of a robot. This work presents a design methodology of a stable adaptive neural controller to overcome the performance degradation for an uncertain nonlinear robot system with actuator failures. The proposed control scheme is based on the Lyapunov stability approach for adaptive control using a GFN (Gaussian function network) to approximate a nonlinear dynamic terms. The proposed controller can improve performance degradation and achieve task completion despite actuator failures and uncertainties. Simulation results are shown to verify the validity and robustness of the proposed control scheme.



**Keywords:** Stable adaptive neural control, Robot system, GFN, Actuator failure, Uncertainty.


## 1 Introduction

Hardware or software failures at actuators as well as uncertainties such as parameter variations and disturbances cause performance degradation of robots.

Fault detection and fault tolerance for robots were dealt with and discussed in [1-4]. The adaptive, robust, and neural control issues for robot systems with uncertainties were discussed in [5-10].

Both actuator failures and uncertainties, which are two factors of performance degradation in a robot system, need to be considered at the same time in the control system design. In most of the previous works, control methods overcoming these two factors at the same time were not yet actively discussed.

In this paper, a stable adaptive neural control scheme for a nonlinear robot system in the presence of actuator failures and uncertainties is developed with guaranteeing the stability, based on adaptive control technique and a GFN. The validity of the proposed scheme is verified through simulation.

## 2 Robot System

The dynamic model of an n-link robot system with actuator failures and uncertainties can be described as

$$M(q)\ddot{q} + F(q,\dot{q}) = u + d(t) = K_a u_c + d(t) \qquad (1)$$

where $q \in \Re^n$ is the position vector of joint coordinates, $M(q)$ is the symmetric positive definite inertial matrix, $F(q,\dot{q}) = C(q,\dot{q})\dot{q} + F_{fr}(\dot{q}) + G(q)$, $C(q,\dot{q})\dot{q}$ represents the centrifugal and Coriolis torques, $F_{fr}(\dot{q}) = F_v\dot{q} + F_d(\dot{q}) + F_s(\dot{q})$ is the vector of friction forces/torques including the viscous, coulomb and static friction forces/torques, respectively, and $G(q)$ is gravitational torques, $u$ is the actual joint torque vector, $u_c$ is the commanded torque vector or controller output vector, and $d(t)$ is an external disturbance vector bounded as $\|d(t)\| \le \theta_d$ where $\theta_d$ is an unknown positive constant. An unknown matrix $K_a \in \Re^{n\times n}$ representing the current joint failure's situation is a bounded nonlinear time-varying diagonal matrix consisting of actuator torque coefficients, in other words, $K_a(t) = diag\left(K_{a1}(t), K_{a2}(t), \cdots, K_{an}(t)\right)$, and $\|K_a\| \le \bar{k}_a$ with an unknown positive constant $\bar{k}_a$.

The block diagram of the robot control system with actuator failures is shown in Fig. 1.

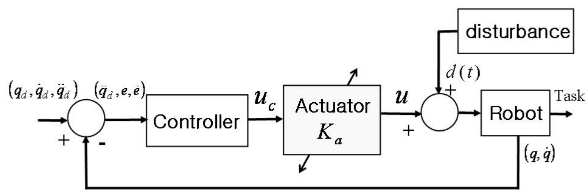


Fig. 1. The robot control system with actuator failures.

The boundary property for each dynamic term of the above dynamic equation (1) is shown as follows.

*Property 1*: There exist positive constants $m_{\min}$, $m_{\max}$, $f_g$, $f_f$, and $f_c$ such that $m_{\min} \le \|M(q)\| \le m_{\max}$, and $\|F(q,\dot{q})\| \le f_g + f_f\|\dot{q}\| + f_c\|\dot{q}\|^2$ [11].

As an ideal case, $K_a$ is an $n \times n$ identity matrix and then $u = u_c$, and it means no actuator failures.

On the contrary, in real robot systems, the commanded torques $u_c$ may not be precisely delivered to the actual torques $u$ due to the hardware or software actuator failures at some joints.

The actuator failures may deteriorate the robot performance. If fault tolerance is not considered in the control system, the more time passes the more degraded the system performance is, ultimately the desired task performance may not be achieved.

In this paper, it is considered that the actuator torque coefficient matrix $K_a$ is not accurately an identity matrix and thus experiences the actuator failures, but it is assumed that $K_a$ does not have any zero diagonal elements. This kind of failure is called as the partial actuator failure.

## 3 Stable Adaptive Neural Control

The joint position error and the augmented error are denoted by $e = q - q_d$ and $s = \dot{e} + \Lambda e$, respectively, where $q_d$ is a desired position vector and $\Lambda \in \Re^{n\times n}$ is a positive definite constant diagonal matrix.

The dynamic equation for the augmented error $s$ is obtained as follows.

$$M(q)\dot{s} = -F(q,\dot{q}) - M(q)\ddot{q}_d + M(q)\Lambda\dot{e} + K_a u_c + d(t). \quad (2)$$

Now, $u_c$ is defined as $u_c = \widehat{K}_a^{-1} v_c$, where $\widehat{K}_a$ represents a guessed nominal model for $K_a$.

Substituting the commanded torque for Eq. (2) and writing it again, it is as follows,

$$M(q)\dot{s} = v_c + \overline{\eta} + \overline{\phi}\,, \quad (3)$$

where $\overline{\eta} = \left(K_a\widehat{K}_a^{-1} - I_n\right)v_c + d(t)$, $\overline{\phi}\left(q,\dot{q},\dot{q}_d,\ddot{q}_d\right) = -F(q,\dot{q}) - M(q)\ddot{q}_d + M(q)\Lambda\dot{e}$, and $I_n$ is an $n \times n$ identity matrix.

*Assumption 1:* There exists an unknown constant $c_0 \geq 0$ such that $\left\|K_a\hat{K}_a^{-1} - I_n\right\| \leq c_0 < 1$.

Let us consider the following Lyapunov function candidate to develop a GFN approximating a nonlinear function.

$$V_1 = s^T M(q)s/2\,. \quad (4)$$

Differentiating Eq. (4) along the solution of the dynamic equation (3),

$$\dot{V}_1 = s^T\left(v_c + \phi + \overline{\eta}\right) = s^T\left(v_c + \eta\right), \quad (5)$$

where the lumped uncertainty $\eta$ is $\eta = \phi + \overline{\eta}$, and

$$\phi(q,\dot{q},q_d,\dot{q}_d,\ddot{q}_d) = \overline{\phi}(q,\dot{q},\dot{q}_d,\ddot{q}_d) + \dot{M}(q,\dot{q})s/2 = \begin{pmatrix}\phi_1 & \phi_2 & \dots & \phi_n\end{pmatrix}^T \in \Re^n\,. \quad (6)$$

The unknown nonlinear function $\phi$ can be expressed by the following GFN.

$$\phi = L(x)w + b + e_a(t,x)\,, \quad (7)$$

where $x \in \Re^m, (m = 5n)$ is the input variable vector such as $q, \dot{q}, q_d, \dot{q}_d$ and $\ddot{q}_d$, getting into the network, and $L(x) \in \Re^{n\times nr}$ is the matrix that has the $r$ Gaussian functions. $w \in \Re^{nr}$ and $b \in \Re^n$ are the desired unknown constant weight and desired unknown constant bias to very approximate the GFN (7) to the nonlinear function $\phi$ (6), together with $L(x) \in \Re^{n\times nr}$. $e_a(t,x) \in \Re^n$ is the approximation error.

The above GFN is illustrated in Fig. 2. $L(x)$ in Eq. (7) is shown as follows.

$$L(x) = \begin{bmatrix} N_1 & N_2 & \cdots & N_r & 0 & 0 & \cdots & 0 & \cdots & \cdots & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & N_1 & N_2 & \cdots & N_r & \cdots & \cdots & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & \cdots & \cdots & \cdots & N_1 & N_2 & \cdots & N_r \end{bmatrix}, \quad (8)$$

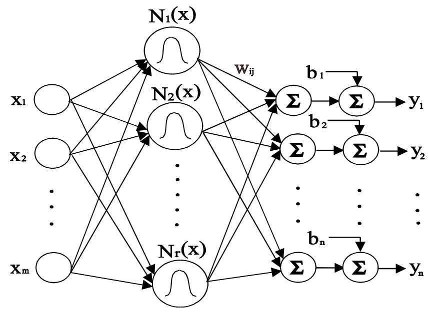


Fig. 2. The structure of the used GFN.

*Assumption 2*: There exist an unknown positive constant vector $\theta_e$ and a known positive function $\psi_e(t,x)$ such that $\left\|e_a(t,x)\right\| \leq \rho_e(t,x) = \theta_e^T\psi_e(t,x)$.

From the structure of the nonlinear function $\phi$ (6) and the GFN (7), it can be easily shown that the above assumption is very reasonable. We can find that the norm of $\phi$ (6) is bounded by a positive function from Property 1. In Eq. (7), the norm of the GFN is also bounded by a positive constant. Therefore, from Property 1, Eqs. (6) and (7), a positive function $\psi_e(t,x)$ can be obtained as follows.

$$\psi_e(t,x) = \begin{pmatrix}1 & \|\dot{q}\| & \|\dot{q}\|^2 & \|\ddot{q}_d\| & \|\dot{e}\| & (\|\dot{q}\|\|s\|)\end{pmatrix}^T \in \Re^6. \quad (9)$$

*Theorem 1:* Under Assumptions 1 and 2, if the following control law and adaptation law are applied to the robot system (1), then the joint position and velocity errors are globally uniformly ultimately bounded.

<u>*Control law*:</u>

$$u_c = \hat{K}_a^{-1}v_c = \widehat{K}_a^{-1}\left(-K_c s - L\hat{w} - \hat{b} - \hat{\rho}\frac{s}{\|s\| + \varepsilon}\right), \quad (10)$$

$$\hat{\rho} = \hat{\theta}^T\psi\,,\ \ \psi = \begin{pmatrix}\|s\| & \|\widehat{w}\| & \left\|\widehat{b}\right\| & \psi_a^T\end{pmatrix}^T \in \Re^{10}, \quad (11)$$

$$\psi_a = \left(\psi_e^T \quad 1\right)^T \in \Re^7, \tag{12}$$

$$\psi_e = \left(1 \quad \|\dot{q}\| \quad \|\dot{q}\|^2 \quad \|\ddot{q}_d\| \quad \|\dot{e}\| \quad (\|\dot{q}\|\|s\|)\right)^T \in \Re^6, \tag{13}$$

where $\widehat{K}_a$ is a guessed nominal actuator torque coefficient matrix as mentioned above and it is usually initially defined as an identity matrix. The gain $K_c \in \Re^{n\times n}$ is a positive definite constant diagonal matrix, $\widehat{w}$ is an estimation weight vector of $w$ and $\widehat{b}$ is an estimation bias vector of $b$, $\varepsilon$ is a small positive constant, and $\widehat{\theta} \in \Re^{10}$ is an estimate for a parameter vector $\theta \in \Re^{10}$.

<u>Adaptation law</u>:

$$\dot{\hat{w}} = \Gamma_w L^T s,\ \dot{\hat{b}} = \Gamma_b s,\ \dot{\hat{\theta}} = \Gamma_\theta\left(\frac{\psi\|s\|^2}{\|s\|+\varepsilon} - \sigma\hat{\theta}\right) \in \Re^{10}, \tag{14}$$

where $\Gamma_w \in \Re^{nr\times nr}$, $\Gamma_b \in \Re^{n\times n}$ and $\Gamma_\theta \in \Re^{10\times 10}$ are positive definite constant diagonal matrices, and $\sigma > 0$ is a small constant.

*Proof:* Let us define an overall Lyapunov function candidate using (4).

$$V = V_1 + V_a = z^T P z / 2 \le \lambda_{\max}(P)\|z\|^2/2, \tag{15}$$

where $z = \left(s^T \quad \tilde{\theta}^T \quad \tilde{w}^T \quad \tilde{b}^T\right)^T$, $V_a = (1-\overline{\theta}_3)\tilde{\theta}^T\Gamma_\theta^{-1}\tilde{\theta}/2 + \tilde{w}^T\Gamma_w^{-1}\tilde{w}/2 + \tilde{b}^T\Gamma_b^{-1}\tilde{b}/2$, $0 \le \overline{\theta}_3 = c_0 < 1$, $\tilde{\theta} = \widehat{\theta} - \theta$, $\tilde{w} = \widehat{w} - w$, and $\tilde{b} = \widehat{b} - b$.

Taking the time derivative of $V$ along the solution of the system and substituting the robot dynamics for the augmented error $s$ (3), the upper-bound on the norm of lumped uncertainty based on Assumption 1 and Assumption 2, and the control laws (10)~(13) and the adaptation laws (14), the following result is made through some manipulations.

$$\begin{aligned}\dot{V} &\le -s^T K_c s - \left(1-\overline{\theta}_3\right)\sigma\tilde{\theta}^T\widehat{\theta} + \overline{h}(\rho,\widehat{\rho},\|s\|) \\ &\le -\lambda_{\min}(Q)\|z\|^2/2 + h(\rho,\widehat{\rho},\|s\|)\end{aligned} \tag{16}$$

where $\tilde{\rho} = \tilde{\theta}^T\psi$, $\widehat{\theta} \in \Re^{10}$, $\psi = \left(\|s\| \quad \|\widehat{w}\| \quad \|\widehat{b}\| \quad \psi_a^T\right)^T \in \Re^{10}$, $\psi_a = \left(\psi_e^T \quad 1\right)^T \in \Re^7$, $\psi_e = \left(1 \quad \|\dot{q}\| \quad \|\dot{q}\|^2 \quad \|\ddot{q}_d\| \quad \|\dot{e}\| \quad (\|\dot{q}\|\|s\|)\right)^T$,

$$\overline{h}(\rho,\widehat{\rho},\|s\|) = \left(\frac{\|s\|\varepsilon}{\|s\|+\varepsilon}\right)\left[\widehat{\rho}\overline{\theta}_3 + \rho\left(1-\overline{\theta}_3\right)\right],\ Q = \begin{pmatrix} 2K_c & 0 \\ 0 & \left(1-\overline{\theta}_3\right)\sigma I_{10}\end{pmatrix},$$

and $\lambda_{\min}(\cdot)$ represents the minimum eigenvalue of its argument, and $h(\rho,\widehat{\rho},\|s\|) = \left(1-\overline{\theta}_3\right)\sigma\theta^T\theta/2 + \overline{h}(\rho,\widehat{\rho},\|s\|)$.

From Eq. (15), Eq. (16) is expressed as

$$\dot{V} \le -\mu V + h(\rho,\widehat{\rho},\|s\|), \tag{17}$$

where $\mu = \lambda_{\min}(Q)/\lambda_{\max}(P)$, $Q$ and $P$ are positive definite matrices, and $\lambda_{\max}(\cdot)$ represents the maximum eigenvalue of its argument.

From the boundedness of the Lyapunov function (15), the augmented error $s(t)$, the parameter errors $\tilde{\theta}(t)$, $\tilde{w}(t)$ and $\tilde{b}(t)$ are bounded as follows. $\|s(t)\| \le \left[2V/\lambda_{\min}(M)\right]^{1/2}$, $\|\tilde{\theta}(t)\| \le \left[2V/\left(1-\overline{\theta}_3\right)\lambda_{\min}(\Gamma_\theta^{-1})\right]^{1/2}$, $\|\tilde{w}(t)\| \le \left[2V/\lambda_{\min}(\Gamma_w^{-1})\right]^{1/2}$, $\|\tilde{b}(t)\| \le \left[2V/\lambda_{\min}(\Gamma_b^{-1})\right]^{1/2}$.

Consequently, since the augmented error $s(t)$ and the parameter errors $\tilde{\theta}(t)$, $\tilde{w}(t)$ and $\tilde{b}(t)$ are globally uniformly ultimately bounded(GUUB), the stable dynamics $s = \dot{e} + \Lambda e$ guarantees that the position and velocity errors $e$ and $\dot{e}$ are also globally uniformly ultimately bounded, respectively. ■

*Remark 1*: In the controller (10), it is reasonable that the guessed nominal actuator torque coefficient matrix $\widehat{K}_a$ is usually initially defined as an identity matrix, because it is hard to expect any kind of actuator failures initially in a robot system and a user can consider the initial actuator states as the normal state.

# 4 Simulation Study

The proposed controller is applied to a three-link robot moving on a horizontal plane shown in Fig. 3. The robotic parameters such as length $(L_i)$, mass $(m_i)$, moment of inertia $(I_i)$, and center position of mass $(L_{ci})$ are $L_i = 0.5(m)$, $m_i = 1(kg)$, $I_i = 0.02083(kgm^2)$ and $L_{ci} = 0.25(m)$, $i = 1,2,3,$ respectively. The viscous, coulomb and static friction coefficients at each joint are assigned to be $0.05(Nm\sec/rad)$, $0.01(Nm)$ and $0.02(Nm)$, respectively.

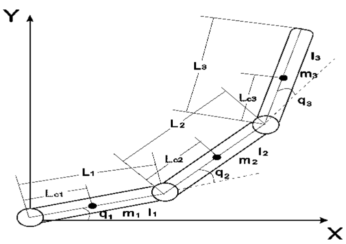


Fig. 3. A three-link planar robot.

The values of the nominal dynamic parameters used in the controllers are set to 50% of the values of the actual dynamic parameters. The nominal values of each friction coefficient are set to zero values. The external disturbance is the random noise of which norm is bounded by $\|d(t)\| \le \sqrt{3}/2$.

The control objective is the joint position control from the initial joint positions $q_1(0) = 0(rad)$, $q_2(0) = 0(rad)$, and $q_3(0) = 0(rad)$ to the final desired joint positions $q_{1d} = 5\pi/6(rad)$, $q_{2d} = \pi/2(rad)$, and $q_{3d} = -2\pi/3(rad)$. The initial joint velocities $\dot{q}(0)$ and the desired joint velocities $\dot{q}_d$ and accelerations $\ddot{q}_d$ of all joints are zeros.

In the Gaussian functions, the 15 basis functions are used. The center positions are randomly initialized and updated by a k-means clustering method. Weights and biases are initialized with very small random numbers and updated by the adaptation laws of the proposed control scheme. The widths are determined as $wid_k = d_{\max} \big/ \sqrt{2 \cdot N_{cen}}$ , where $d_{\max}$ is the maximum distance between the chosen centers and $N_{cen}$ is the number of centers.

The simulation scenario is given as follows. Total execution time is 10 (sec). Initially, no actuator failures are assumed. From the initial time to 3 (sec), the robot has the normal states without failures. The actuator failures at all joints occur at 3 (sec) and continue from 3 (sec) to 10 (sec). The actuator torque coefficients are shown in Fig. 4.

The guessed nominal actuator torque coefficient matrix $\widehat{K}_a$ is defined as an identity matrix.

In this simulation, the proposed adaptive neural control scheme and PD control method are compared, and Fig. 5 and Fig. 6 show the simulation results for each control method.

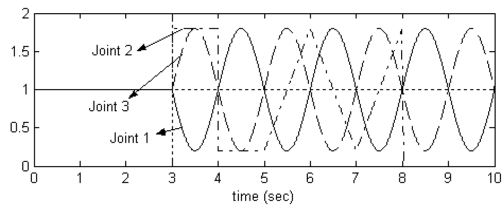


Fig. 4. Actual actuator torque coefficients $(K_a)$ .

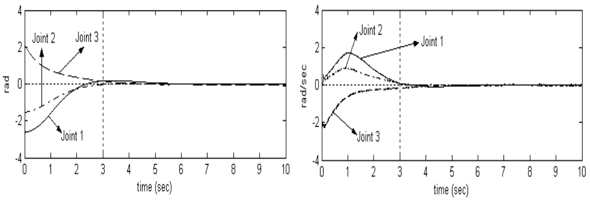


Fig. 5-(a). Joint position errors $(e)$.

Fig. 5-(b). Joint velocity errors $(\dot{e})$.

Fig. 5. Control results using the proposed controller.

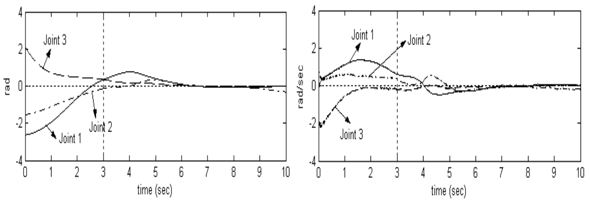


Fig. 6-(a). Joint position errors $(e)$.

Fig. 6-(b). Joint velocity errors $(\dot{e})$.

Fig. 6. Control results using the PD controller.

As shown in Figs. 5-(a) and 5-(b), it is found that the position and velocity errors decrease to very small neighborhoods of zero even though the actuator failures occur under the uncertainties. From Figs. 6-(a) and 6-(b), it is shown that the position and velocity errors do not satisfactorily converge to very small neighborhoods of zeros due to actuator failures and uncertainties.

## 5 Conclusions

This work has presented a stable adaptive neural control scheme for a robot system with performance degradation due to actuator failures and uncertainties. The proposed controller can improve the performance in the presence of actuator failures and uncertainties, and it achieves task completion.

It has been observed that the proposed control scheme is valid and robust under the actuator failures and uncertainties through simulation study.

This work is applicable to an uncertain remote robot system of which independent actuators are partially failed. In other words, for an uncertain robot with partially failed actuators in remote sites, the actuator failures are compensated and the task can be completed by the proposed controller, without human intervention.

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