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PLENARY LECTURE

Adaptive Intelligent Control of Robot Manipulators

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Abstract

In this paper, we study the performance of two adaptive robot control algorithms, namely the adaptive algorithm by Slotine and Li [20] and the proposed Indirect Adaptive Fuzzy Control algorithm. In Slotine and Li's method, the algorithm consists of a PD feedback and a full dynamics feedforward part, with the unknown manipulator and payload parameters being estimated on-line. This algorithm depends heavily on the particular structure of manipulator dynamics and needed three simplifying properties to derive the adaptive law. The proposed Indirect Adaptive Fuzzy Controller (IAFC) uses a fuzzy system as an approximator for the robot dynamics. The adaptive law updates the unknown dynamics online. The estimated dynamics are then used in the control law. The predominant concern of the two algorithms is to reduce the tracking errors. In particular, they require no feedback of joint accelerations. Theoretical results and simulation studies on a SEIKO D-TRAN 3000 series robot manipulator show that both methods are robust and stable. The IAFC outperforms the adaptive controller of [20] in mass variation.

1. INTRODUCTION

The motivation to make robot manipulators capable of handling large loads in the presence of uncertainty on the mass properties of the load or its exact position in the end-effector has spurred much research on adaptive robot control. The equations to model robot dynamics are highly nonlinear and coupled and the derivation is difficult for large degrees of freedom. Furthermore, the system's parameters are variable and modeling errors exist due to unknown static friction forces at the joints and uncertainty in the link parameters. At high speed, Coriolis and centrifugal forces must be taken into account since they introduce additional nonlinearities. The inertia load at each joint varies significantly with the position of the arm. Parametric uncertainties will be present due to imprecise knowledge of the manipulator mass properties, unknown loads, uncertainty in the load position of the end-effector, and inaccuracies in the torque constants of the actuators [1]. Structural uncertainties arise from the presence of high-frequency unmodeled dynamics, resonant modes, actuator dynamics, flexibilities in the links, or finite sampling rates. Additive disturbances are present in the form of coulomb friction, gravitational forces, measurement noise, backlash, or actuator saturation [2]. In the presence of such uncertainties, linear feedback controllers, for example, PD or PID controllers, cannot provide consistent performance.

Over the years, different approaches have been considered in designing control systems for dealing with uncertainties in robotics systems [3]-[33]. In [3]-[7], ignoring the dynamic complexity, linearizing time-varying models about the reference trajectories and assuming that during the adaptation process, the elements of the linearized system remain constant. However, for fast motion of robots, this assumption is not valid. The controllers of [8] must use unbounded feedback gains for the convergence of the tracking error to zero. The control algorithms of [9]-[10] do not yield zero tracking error. Craig [11], Khosla and Kanade [12] and Atkeson [13] exploited and extensively used the known structure of the system dynamics. However, the requirement to estimate the joint accelerations makes the algorithms computationally heavy. The discontinuous control law [14] causes the trajectory to chatter along the sliding surface. An, Atkeson and Hollerbach [15] demonstrated the importance of accurate modeling in force and trajectory control to avoid performance degradation or instability in the case of revolute manipulators when utilizing robust, model-based non-adaptive control algorithms. Karam [16] showed an interesting adaptive controller which has an explicit relationship between the process parameters and the PID controller's gains.

Authors of [17] and [18] further extended the control scheme in [16]. But, a linear ARMA model is used and the non-linear dynamics is supposed to be compensated using feedforward (or feedback) compensation. However, the fundamental problem still exists as the dynamics model suffers from inaccuracy due to unknown payloads. In 1987, Spong [19] proposed an alternative formulation for the adaptive inverse dynamics control law which overcomes the assumption of boundedness of the inverse estimated inertia matrix. But Spong's algorithm assumes an inverse dynamics model with a priori estimated values of robot dynamics and off-line computations. Slotine and Li [20] developed an adaptive version of the sliding control algorithm which consists of a PD feedback law and a full dynamics feedforward compensation law, with the unknown manipulator and payload parameters being estimated on-line. However, this method makes extensive use of the equations of motion to model the robot dynamics.

In [23], the authors apply the hyperstability concept to provide local asymptotic tracking. In [24], a Lyapunov MRAC scheme is implemented under the assumption that elements of the closed-loop system matrix are sufficiently close to those of the reference model. Decentralized adaptive control using high-gain adaptation algorithm is treated in [25]. An adaptive scheme for small perturbations around a known nominal trajectory is considered in [26]. A perturbation method is applied to a linearised model in [27]. Learning theory is applied in [28], and hybrid adaptive control schemes of manipulators are considered in [29,30]. Another interesting approach has been suggested in [31]-[35] where the theory of variable structure systems is used. This approach takes into account input signal saturation since the input is switched between its minimum and maximum values. Undesirable chattering of the input signal can be overcome by using a continuous rather than a discontinuous control law [10,33]. Such an approach ensures that both position and velocity errors go to zero asymptotically. Unfortunately, these existing schemes again require the mathematical representation of the plant to be known and are unable to capture and incorporate the approximate, qualitative aspects of human knowledge, which can be an important source of information.

During the past decade, intelligent control methodologies have gradually been devised to solve a number of complicated problems, in particular, control of robot manipulators which conventional control methodologies find it difficult or impossible to handle. In the event that the solution seems feasible, the cost of implementation is usually too high. These methods often use biologically motivated techniques and processes, and are generally referred to as neural networks or some kind of learning schemes [36]-[39]. Unlike general conventional schemes which are based on complete control theory and algorithmic structure, they are in general hardly evaluated experimentally. Therefore, it is imperative to make efforts in bridging the gap between the conventional control schemes and the intelligent ones [40]. Recently, analysis-based intelligent control has attracted enormous research interests [41,42]. Ideas behind those schemes are to strengthen their theoretical basis, but at the price of expensive implementation by using massive networks and extensive rule-tables. These lead to difficulties in real-time implementation due to practical limitations such as long computation time and excessive memory space usage. On the other hand, the heuristic nature of intelligent control such as fuzzy logic often offers much benefits for control systems. An important advantage of using fuzzy logic control is that fuzzy theories can capture the approximate, qualitative aspects of human knowledge and reasoning without the need for precise mathematical representations of the plant to be known. Apparently, such control strategy provides a rather feasible alternative for a plant like a robot manipulator which is extremely complex.

The trend in robot control design is to lift the limits of performance while decreasing the required a priori knowledge of the robot's dynamics. In this paper, an indirect adaptive fuzzy robot control algorithm which consists of a fuzzy controller and an adaptive law to update the controller parameters on-line is developed. This controller assumes that the robot dynamics are completely unknown and no information on the uncertainty is available except the boundary of the dynamics.

The advantages of the proposed Indirect Adaptive Fuzzy Controller (IAFC) over Slotine's method are :

1. Fuzzy control is a model-free approach. It does not require the exact mathematical model of the robot dynamics.
2. Fuzzy control provides nonlinear controllers which are well justified due to the Universal Approximation Theorem, see [21] for details. These fuzzy controllers are general enough to perform any nonlinear control actions.
3. The fuzzy system, a rule-based algorithm, can incorporate linguistic fuzzy information from human experts to speed up adaptation.

The paper is organized as follows : Section 2 outlines a systematic procedure of developing the IAFC to achieve the control objectives. Simulation results of an industrial SCARA robot, SEIKO D-TRAN 3000 series robot are presented in Section 3. Section 4 contains concluding remarks.

2. INDIRECT ADAPTIVE FUZZY ROBOT CONTROLLER

2.1 Control Objectives

The control objectives are to determine a feedback control signal $\tau = t(q / f)$ and an adaptive law for adjusting the parameter vector ϕ such that :

1. The closed-loop system must be globally stable in the sense that all variables $\theta(t)$, $\phi(t)$ and $\tau(\theta/\phi)$ must be uniformly bounded; that is, $|\theta(t)| \leq M_\theta < \infty$, $|\phi(t)| \leq M_\phi < \infty$ and $|\tau(\theta/\phi)| \leq M_\tau < \infty$ for all $t \geq 0$ where M_θ, M_f and M_t are parameters specified by the designer.
2. The tracking error, $e = q_m - q$ should be as small as possible under the constraints in the previous objective where q_m and q are the desired and actual angular positions respectively.

In the sequel, we will show how to achieve these objectives.

2.2 The Manipulator Dynamics

The manipulator can be modelled as a set of n rigid bodies connected in a serial chain with friction acting at the joints. The vector equation describing the n x 1 vectors of joint forces or torques supplied by the actuators is given by

$$\tau = M(\theta)\ddot{\theta} + Q(\theta, \dot{\theta}) \tag{3.1}$$

where $q = [q_1, q_2, \ldots, q_n]^T$ is the n x 1 vector of joint positions, the matrix, $M(q)$ is an n x n symmetric positive definite manipulator mass matrix and the vector $Q(\theta, \dot{\theta})$ represents forces or torques arising from centrifugal, Coriolis, gravitational and frictional forces. Since $M(q)$ is positive definite and is invertable, it follows from Eq. (3.1) that

$$\ddot{q} == F(q, \dot{q}) + G(q)t \tag{3.2}$$

where

$$F(\theta, \dot{\theta}) = -M^{-1}(\theta)Q(\theta, \dot{\theta}) \text{ and } G(\theta) = M^{-1}(\theta)$$

Note that $G(\theta)$ is also an n x n symmetric positive definite matrix.

Define $E = (e_1, e_2, \ldots e_n)$ and $\dot{E} = (\dot{e}_1, \dot{e}_2, \ldots \dot{e}_n)$ where $e_i = \theta_{mi} - \theta_i$, $i = 1,2,\ldots\ldots,n$ and q_{mi} and q_i are the ith component of q_m and q respectively. If $F(\theta, \dot{\theta})$ and $G(\theta)$ are known, we can use the well-known computed torque control law

$$\tau = G^{-1}(\theta)\left[-F(\theta, \dot{\theta}) + \ddot{\theta}_m + K_v\dot{E} + K_pE\right] \tag{3.3}$$

and applying it to Eq. (3.2) yields

$$\ddot{E} + K_v\dot{E} + K_pE = 0 \tag{3.4}$$

where K_v and K_p are n x n diagonal gain matrices whose entries are constants.

2.3 Certainty Equivalent Controller

Since the nonlinear functions $F(\theta, \dot{\theta})$ and $G(\theta)$ are unknown, we replace $F(\theta, \dot{\theta})$ and $G(\theta)$ by the fuzzy logic systems $\hat{F}(\theta, \dot{\theta}/\phi)$ and $\hat{G}(\theta/\phi)$ which assume the following form:

$$f(\underline{x}) = \frac{\sum_{l=1}^{M} y^l \left(\prod_{i=1}^{n} \exp\left[-\left(\frac{x_i - x_i^l}{\sigma_i^l} \right)^2 \right] \right)}{\sum_{l=1}^{M} \left(\prod_{i=1}^{n} \exp\left[-\left(\frac{x_i - x_i^l}{\sigma_i^l} \right)^2 \right] \right)} \tag{3.5}$$

where $f(\underline{x})$ is the fuzzy logic system with Gaussian membership function, centre average defuzzifier and product-inference rule, and y^l, x_i^l and s_i^l are adjustable parameters, see [21] for details.

Then, the resulting control law is :

$$\tau_c = \hat{G}^{-1}(\theta/\phi)\left[-\hat{F}(\theta,\dot{\theta}/\phi) + \ddot{\theta}_m + K_v\dot{E} + K_p E\right] \tag{3.6}$$

which is called certainty equivalent controller in the adaptive control literature. With τ in Eq. (3.2) being substituted by τ_c as defined in Eq. (3.6) and after some manipulations, the closed-loop error dynamics becomes :

$$\ddot{E} = -K_v\dot{E} - K_p E + \left[\hat{F}(\theta,\dot{\theta}/\phi) - F(\theta,\dot{\theta})\right] + \left[\hat{G}(\theta/\phi) - G(\theta)\right]\tau_c \tag{3.7}$$

The error dynamics can be expressed in the following state-space form:

$$\dot{X} = AX + B\left[\left(\hat{F}(\theta,\dot{\theta}/\phi) - F(\theta,\dot{\theta})\right) + \left(\hat{G}(\theta/\phi) - G(\theta)\right)\tau_c\right] \tag{3.8}$$

where $X = (e_1, \dot{e}_1, e_{2,}, \ldots, \dot{e}_n)^T$ and

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 & \ldots \\ K_{p1} & K_{v1} & 0 & 0 & \cdots \\ 0 & 0 & 0 & 1 & \cdots \\ 0 & 0 & K_{p2} & K_{v2} & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix}, \quad B = \begin{bmatrix} 0 & 0 & \cdots \\ 1 & 0 & \cdots \\ 0 & 0 & \cdots \\ 0 & 1 & \cdots \\ \cdots & \cdots & \cdots \end{bmatrix}$$

with K_p and K_v chosen such that A is a stable matrix. There exists a unique $2n$ x $2n$ positive definite symmetric P matrix which satisfies the Lyapunov equation [20] :

$$A^T P + PA = -Q \tag{3.9}$$

where Q is an arbitrary $2n$ x $2n$ positive definite matrix. Let the Lyapunov function candidate be

$$V_e = \frac{1}{2} X^T P X \tag{3.10}$$

Differentiating Eq. (3.10) with respect to time and using Eq. (3.9) leads to

$$\dot{V}_e = \frac{1}{2}\dot{X}^T PX + \frac{1}{2}X^T P\dot{X}$$

$$= -\frac{1}{2}X^T QX + X^T PB\left[\left(\hat{F}(\theta,\dot{\theta}/\phi) - F(\theta,\dot{\theta})\right) + \left(\hat{G}(\theta/\phi) - G(\theta)\right)\tau_c\right] \qquad (3.11)$$

2.4 Supervisory Control

In order for the system to be bounded, we require that V_e must be bounded. But from Eq. (3.11), it is very difficult to design τ_c such that $\dot{V}_e \le 0$ when $V_e > \overline{V}$ which is specified by the designer. By appending another control term called supervisory control, τ_s to τ_c, we can solve the problem. The final control law is

$$\tau = \tau_c + \tau_s \qquad (3.12)$$

The purpose of the supervisory control law, τ_s is to force $\dot{V}_e \le 0$ whenever $V_e > \overline{V}$.

Concerning the proposed final control law, we have the following lemma:

Lemma 1 : Consider the manipulator dynamics given by Eq. (3.2) and the proposed IAFC whose control law is given by Eq. (3.12). For a prescribed $\overline{V}$, we can always guarantee that the closed-loop system is Bounded-Input-Bounded-Output (BIBO) stable.

Proof: See Appendix.

Lemma 2 : A system with a smaller value of the Lyapunov function, V_e would have smaller steady-state errors.

Proof : As shown in [20], the Lyapunov function, V_e, a scalar quantity reflects the mechanical energy of the system and the magnitude of the error vector, *X*, at all times. Using this fact, the result follows readily.

Now, we state the main theorem concerning the performance of IAFC.

Theorem 1 : Using the proposed IAFC with the control law given by Eq. (3.12), steady-state tracking errors of the closed-loop system are guaranteed to be smaller than those of the Slotine and Li's method.

Proof : Suppose that the Lyapunov function for the Slotine and Li's method assumes a specific value, V_{e2} when the controller is designed. It follows from Lemma 1 that using the IAFC, we can always choose V_{e1} so that $V_{e1} < V_{e2}$. That the IAFC will achieve smaller steady-state errors than the Slotine and Li's method follows readily on using Lemma 2.

2.5 Adaptive Law

In this section, we show how to determine an adaptive law to update the fuzzy logic system of Eq. (3.5) using the Lyapunov theory. We define

$$\phi_f^* = \arg\min_{\phi_f \in \Omega_f} \left[\sup_{\theta \in \Re^n} |\hat{F}(\theta, \dot{\theta} / \phi_f) - F(\theta, \dot{\theta})| \right] \tag{3.13}$$

$$\phi_g^* = \arg\min_{\phi_g \in \Omega_g} \left[\sup_{\theta \in \Re^n} |\hat{G}(\theta / \phi_g) - G(\theta)| \right] \tag{3.14}$$

where Ω_f and Ω_g are constraint sets for θ_f and θ_g , which are specified by the designer, respectively. We require ϕ_f and ϕ_g to be bounded such that

$$\Omega_f = \left\{ \phi_f : |\phi_f| \le M_f, \sigma_i^l \ge \sigma \right\} \tag{3.15}$$

$$\Omega_g = \left\{ \phi_g : |\phi_g| \le M_g, \sigma_i^l \ge \sigma \right\} \tag{3.16}$$

Define the minimum approximation error as

$$w = \left(\hat{F}(\theta, \dot{\theta} / \phi_f^*) - F(\theta, \dot{\theta}) \right) + \left(\hat{G}(\theta / \phi_g^*) - G(\theta) \right) \tau_c \tag{3.17}$$

Then, the error dynamics becomes

$$\begin{aligned} \dot{X} = AX - BG(\theta)\tau_s + B\Big[& \left(\hat{F}(\theta, \dot{\theta} / \phi_f) - \hat{F}(\theta, \dot{\theta} / \phi_f^*) \right) \\ & + \left(\hat{G}(\theta / \phi_g) - \hat{G}(\theta / \phi_g^*) \right) \tau_c + w \Big] \end{aligned} \tag{3.18}$$

We will approximate $\hat{F}(\theta, \dot{\theta} / \phi_f)$ and $\hat{G}(\theta / \phi_g)$ using Taylor series expansions around ϕ_f and ϕ_g, i.e. we have

$$\hat{F}(q, \dot{q} / f_f) - \hat{F}(q, \dot{q} / f_f^*) = d_f^T \left(\frac{¶\hat{F}(q, \dot{q} / f_f)}{¶f_f} \right) + O(|d_f|^2)$$

$$= \begin{bmatrix} \delta_{f1}^T \dfrac{\partial \hat{f}_1(\theta, \dot{\theta} / \phi_{f1})}{\partial \phi_{f1}} \\ \delta_{f2}^T \dfrac{\partial \hat{f}_2(\theta, \dot{\theta} / \phi_{f2})}{\partial \phi_{f2}} \\ \vdots \\ \delta_{fn}^T \dfrac{\partial \hat{f}_n(\theta, \dot{\theta} / \phi_{fn})}{\partial \phi_{fn}} \end{bmatrix} + O(|\delta_f|^2) \tag{3.19}$$

$$\hat{G}(\theta / \phi_g) - \hat{G}(\theta / \phi_g^*) = \delta_g^T \left(\frac{\partial \hat{G}(\theta / \phi_g)}{\partial \phi_g} \right) + O(|\delta_g|^2)$$

$$= \begin{bmatrix} \delta_{g1}^T \left(\dfrac{\partial \hat{G}_1(\theta / \phi_{g1})}{\partial \phi_{g1}} \right) \\ \delta_{g2}^T \left(\dfrac{\partial \hat{G}_2(\theta / \phi_{g2})}{\partial \phi_{g2}} \right) \\ \vdots \\ \delta_{gn}^T \left(\dfrac{\partial \hat{G}_n(\theta / \phi_{gn})}{\partial \phi_{gn}} \right) \end{bmatrix} + O(|\delta_g|^2)$$

$$= \begin{bmatrix} \delta_{g11}^T \dfrac{\partial \hat{g}_{11}(\theta/\phi_{g11})}{\partial \phi_{g11}} & \delta_{g12}^T \dfrac{\partial \hat{g}_{12}(\theta/\phi_{g12})}{\partial \phi_{g12}} & \cdots & \delta_{g1n}^T \dfrac{\partial \hat{g}_{1n}(\theta/\phi_{g1n})}{\partial \phi_{g1n}} \\ \delta_{g21}^T \dfrac{\partial \hat{g}_{21}(\theta/\phi_{g21})}{\partial \phi_{g21}} & \delta_{g22}^T \dfrac{\partial \hat{g}_{22}(\theta/\phi_{g22})}{\partial \phi_{g22}} & \cdots & \delta_{g2n}^T \dfrac{\partial \hat{g}_{2n}(\theta/\phi_{g2n})}{\partial \phi_{g2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{gn1}^T \dfrac{\partial \hat{g}_{n1}(\theta/\phi_{gn1})}{\partial \phi_{gn1}} & \delta_{gn2}^T \dfrac{\partial \hat{g}_{n2}(\theta/\phi_{gn2})}{\partial \phi_{gn2}} & \cdots & \delta_{gnn}^T \dfrac{\partial \hat{g}_{nn}(\theta/\phi_{gnn})}{\partial \phi_{gnn}} \end{bmatrix} + O(|\delta_g|^2) \tag{3.20}$$

where

$$\delta_f = \phi_f - \phi_f^*$$

$$\delta_g = \phi_g - \phi_g^*$$

and $O(|\delta_f|^2)$, $O(|\delta_g|^2)$ are higher order terms. Substituting Eqs. (3.19) and (3.20) into Eq. (3.18), the error dynamics becomes

$$\begin{aligned} \dot{X} = AX - BG(\theta)\tau_s + Bv + B_1 & \left[\left(\delta_{f1}^T \frac{\partial \hat{f}_1(\theta, \dot{\theta}/\phi_{f1})}{\partial \phi_{f1}} \right) + \left(\delta_{g1}^T \frac{\partial \hat{G}_1(\theta/\phi_{g1})}{\partial \phi_{g1}} \right) \tau_c \right] + \ldots + \\ & B_n \left[\left(\delta_{fn}^T \frac{\partial \hat{f}_n(\theta, \dot{\theta}/\phi_{fn})}{\partial \phi_{fn}} \right) + \left(\delta_{gn}^T \frac{\partial \hat{G}_n(\theta/\phi_{gn})}{\partial \phi_{gn}} \right) \tau_c \right] \end{aligned} \tag{3.21}$$

where

$$v = w + O(|\delta_f|^2) + O(|\delta_g|^2)\tau_c$$

$$B = \begin{bmatrix} B_1 & B_2 & \cdots & B_n \end{bmatrix} \quad \text{and} \quad B_1 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}, \quad B_2 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}, \ldots, \quad B_n = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}$$

Now, consider the Lyapunov candidate of the form

$$V=\frac{1}{2}X^TPX+\frac{1}{2\gamma_1}\delta_{f1}^T\delta_{f1}+\ldots+\frac{1}{2\gamma_n}\delta_{fn}^T\delta_{fn}+\frac{1}{2\alpha_1}\delta_{g1}^T\delta_{g1}+\ldots+\frac{1}{2\alpha_n}\delta_{gn}^T\delta_{gn} \tag{3.22}$$

where $\gamma_1,\gamma_2,\ldots\gamma_n$ and $\alpha_1,\alpha_2,\ldots\alpha_n$ are positive adaptive gains. The time derivative of V along the trajectory of Eq. (3.25) is

$$\begin{aligned}
\dot{V} \;=\; & -\frac{1}{2}X^TQX-G(\theta)X^TPB\tau_s+X^TPBv \\
& +\frac{1}{\gamma_1}\delta_{f1}^T\left[\dot{\phi}_{f1}+\gamma_1X^TPB_1\frac{\partial\hat{f}_1(\theta,\dot{\theta}/\phi_{f1})}{\partial\phi_{f1}}\right] \\
& +\frac{1}{\alpha_1}\delta_{g1}^T\left[\dot{\phi}_{g1}+\alpha_1X^TPB_1\frac{\partial\hat{G}_1(\theta/\phi_{g1})}{\partial\phi_{g1}}\tau_c\right]+\ldots \\
& +\frac{1}{\gamma_n}\delta_{fn}^T\left[\dot{\phi}_{fn}+\gamma_nX^TPB_n\frac{\partial\hat{f}_n(\theta,\dot{\theta}/\phi_{fn})}{\partial\phi_{fn}}\right] \\
& +\frac{1}{\alpha_n}\delta_{gn}^T\left[\dot{\phi}_{gn}+\alpha_nX^TPB_n\frac{\partial\hat{G}_n(\theta/\phi_{gn})}{\partial\phi_{gn}}\tau_c\right]
\end{aligned} \tag{3.23}$$

where

$$\begin{matrix}\dot{\delta}_{f1}=\dot{\phi}_{f1} & & \dot{\delta}_{g1}=\dot{\phi}_{g1}\\ \vdots & \text{and} & \vdots \\ \dot{\delta}_{fn}=\dot{\phi}_{fn} & & \dot{\delta}_{gn}=\dot{\phi}_{gn}\end{matrix}$$

If we choose the adaptive law as

$$\begin{aligned}
\dot{\phi}_{f1}&=-\gamma_1X^TPB_1\frac{\partial\hat{f}_1(\theta,\dot{\theta}/\phi_{f1})}{\partial\phi_{f1}}\\
&\vdots\\
\dot{\phi}_{fn}&=-\gamma_nX^TPB_n\frac{\partial\hat{f}_n(\theta,\dot{\theta}/\phi_{fn})}{\partial\phi_{fn}}
\end{aligned} \tag{3.24}$$

$$\begin{aligned}
\dot{\phi}_{g1}&=-\alpha_1X^TPB_1\frac{\partial\hat{G}_1(\theta/\phi_{g1})}{\partial\phi_{g1}}\tau_c\\
&\vdots\\
\dot{\phi}_{gn}&=-\alpha_nX^TPB_n\frac{\partial\hat{G}_n(\theta/\phi_{gn})}{\partial\phi_{gn}}\tau_c
\end{aligned} \tag{3.25}$$

then from Eq. (3.23), we have

$$\dot{V} \le -\frac{1}{2} X^T QX + X^T PBv \tag{3.26}$$

Using the Universal Approximation Theorem and neglecting higher order terms, $\dot{V}$ can be approximated to be

$$\dot{V} \le -\frac{1}{2} X^T QX \tag{3.27}$$

Our final question is how to constraint ϕ_f and ϕ_g within the sets $\mathbf{\Omega}_f$ and $\mathbf{\Omega}_g$ respectively. Since $\hat{F}(\theta,\dot{\theta}/\phi)$ is bounded and $\hat{G}(\theta/\phi)$ is positive definite and if we keep $\phi_f \in \mathbf{\Omega}_f$ and $\phi_g \in \mathbf{\Omega}_g$, then τ_c and τ_s will be also bounded and the error (X) is bounded due to the supervisory control law, τ_s. But, from the adaptive law of Eq. (3.26) and Eq. (3.27), we cannot keep $\phi_f \in \mathbf{\Omega}_f$ and $\phi_g \in \mathbf{\Omega}_g$. We solve the problem by using the parameter projection algorithm of [22]. The idea is that if the parameter vectors $\mathbf{\Omega}_f$ and $\mathbf{\Omega}_g$ are within the constraint sets or on the boundaries of the constraint sets but moving toward their interiors, we can use the simple adaptive law of Eq. (3.26) and Eq. (3.27). Otherwise, we use the parameter projection algorithm to modify the adaptive law of Eq.(3.26) and Eq. (3.27) as follows :

$$\begin{aligned} \dot{\phi}_{f1} &= -\gamma_1 X^T PB_1 \frac{\partial \hat{f}_1(\theta,\dot{\theta}/\phi_{f1})}{\partial \phi_{f1}} + \gamma_1 X^T PB_1 \frac{\phi_{f1}\phi_{f1}^T}{|\phi_{f1}|^2} \frac{\partial \hat{f}_1(\theta,\dot{\theta}/\phi_{f1})}{\partial \phi_{f1}} \\ &\vdots \\ \dot{\phi}_{fn} &= -\gamma_n X^T PB_n \frac{\partial \hat{f}_n(\theta,\dot{\theta}/\phi_{fn})}{\partial \phi_{fn}} + \gamma_n X^T PB_n \frac{\phi_{fn}\phi_{fn}^T}{|\phi_{fn}|^2} \frac{\partial \hat{f}_n(\theta,\dot{\theta}/\phi_{fn})}{\partial \phi_{fn}} \end{aligned} \tag{3.28}$$

$$\begin{aligned} \dot{\phi}_{g1} &= -\alpha_1 X^T PB_1 \frac{\partial \hat{G}_1(\theta/\phi_{g1})}{\partial \phi_{g1}} \tau_c + \alpha_1 X^T PB_1 \frac{\phi_{g1}\phi_{g1}^T}{|\phi_{g1}|^2} \frac{\partial \hat{G}_1(\theta/\phi_{g1})}{\partial \phi_{g1}} \tau_c \\ &\vdots \\ \dot{\phi}_{gn} &= -\alpha_n X^T PB_n \frac{\partial \hat{G}_n(\theta/\phi_{gn})}{\partial \phi_{gn}} \tau_c + \alpha_n X^T PB_n \frac{\phi_{gn}\phi_{gn}^T}{|\phi_{gn}|^2} \frac{\partial \hat{G}_n(\theta/\phi_{gn})}{\partial \phi_{gn}} \tau_c \end{aligned} \tag{3.29}$$

such that the parameter vectors will remain inside the constraint sets.

3. Simulation Results

The Indirect Adaptive Fuzzy Controller (IFAC) in Section 2 was simulated to study the stability, robustness and feasibility aspects of this control algorithm. An industrial SCARA robot, SEIKO TT-3000, whose dynamic model has been identified using least square method and verified experimentally in [43], was used in the simulation study.

3.1 Overview of the SEIKO TT-3000 SCARA Robot

The SEIKO D-TRAN 3000 series robot is a 4-axis, closed-loop DC servo SCARA (Selectively Compliance Assembly Robot Arm) manipulator. Each of the four axes provides a different motion and contributes to one degree of freedom of the robot arm, as depicted in Figure 4.1. The main characteristics of the TT-3000 SCARA robot are its high precision, repeatability and speed.

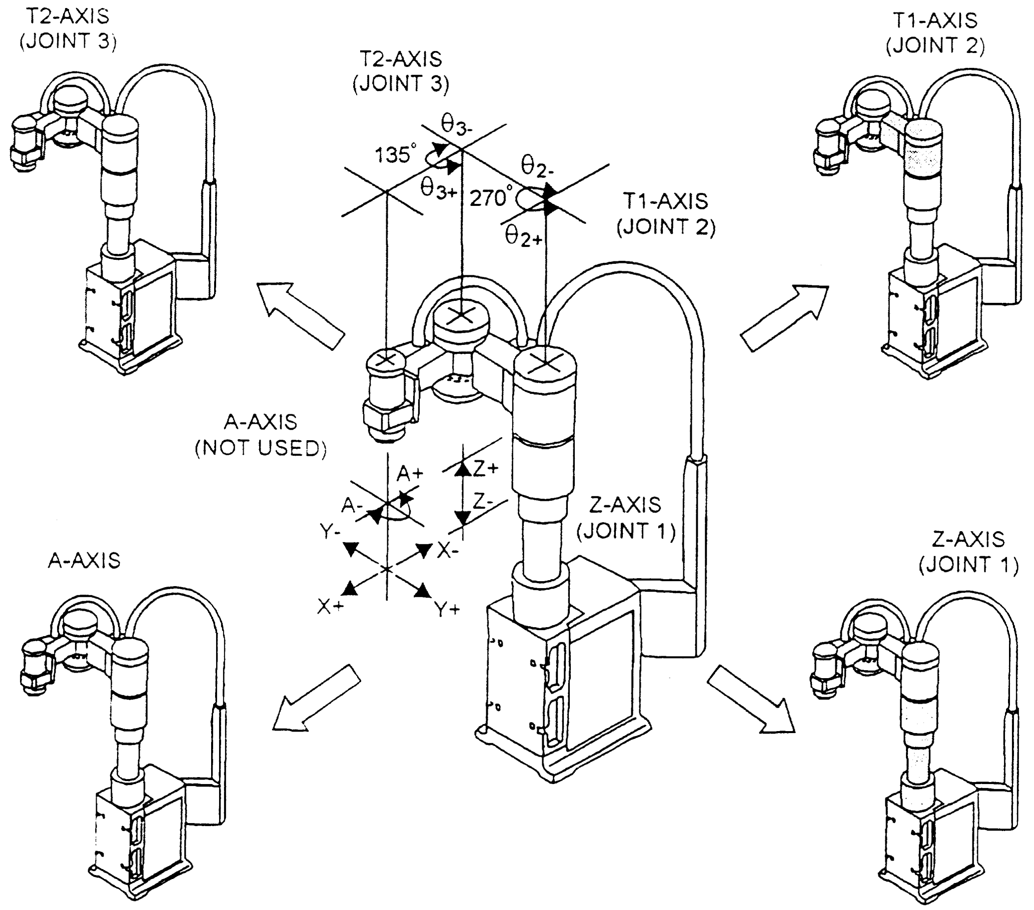


Figure 4.1 : The SEIKO D-Tran TT-3000 SCARA robot arm

The basic SCARA geometry is realised by arranging two revolute joints (T1 and T2 Axes) and one prismatic joint (Z-Axis) in such a way that all axes of motion are parallel. The Z-Axis provides the vertical stroke of the manipulator while both the T1 and T2-Axes provide the plane rotation. The SCARA characterises the mechanical features of a structure offering high stiffness to vertical loads and compliance to horizontal loads. In such a configuration, the gravitational load, Coriolis and centrifugal forces do not stress the structure as much as they would if the axes are horizontal. This advantage is very important for manipulators used in high speeds and high precision tasks. A third revolute joint (A-Axis) of the TT-3000 at the end-effector only serves to provide additional flexibility to the manipulator task programmability.

3.2 Dynamic Model of the SEIKO TT-3000 SCARA Robot

The dynamics of an *n*th joint robot arm is generally expressed in the form of :

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + F_v\dot{q} + F_c = t \tag{4.1}$$

where

$M(q)$ is the *n*x*n* inertia matrix of the manipulator,

$C(q,\dot{q})$ is the *n*x*n* matrix of centrifugal and Coriolis terms,

$G(q)$ is the *n*x*1* vector of gravity terms,

F_v is the *n*x*1* vector of viscous friction terms,

F_c is the *n*x*1* vector of coulomb friction terms and

t is the *n*x*1* vector of input torque (generated by the joint motor)

The two revolute joints (T1 and T2-Axis) of the Seiko TT-3000 SCARA robot form a two-link arm. This two-link manipulator is a nonlinear system and there exists nonlinear coupling between the two links. Therefore, this two-link arm is suitable to be used for studying the effectiveness of the proposed IAFC.

The dynamic model of the TT-3000 SCARA robot arm has been developed by [43] with most of its dynamic parameters determined and verified through extensive experiments. The model of the T1 and T2-Axis (Joints 2 and 3) are reproduced here:

$$\begin{bmatrix} 0.653 + 0.670\cos q_3 & 0.204 + 0.335\cos q_3 \\ 0.204 + 0.335\cos q_3 & 0.204 \end{bmatrix} \begin{bmatrix} \ddot{q}_2 \\ \ddot{q}_3 \end{bmatrix} + \begin{bmatrix} -0.335(2\dot{q}_2\dot{q}_3 + \dot{q}_3^2)\sin q_3 \\ 0.335\dot{q}_2^2 \sin q_3 \end{bmatrix} + \begin{bmatrix} F_{V2}\dot{q}_2 \\ F_{V3}\dot{q}_3 \end{bmatrix} + \begin{bmatrix} F_{C2} \\ F_{C3} \end{bmatrix} = \begin{bmatrix} t_2 \\ t_3 \end{bmatrix} \tag{4.2}$$

where

viscous coefficients for joint *i* are given by:

$$F_{Vi} = \begin{cases} f_{vi-} & \text{for angular motion in the } -q_i \text{ direction for joint } i \\ f_{vi+} & \text{for angular motion in the } +q_i \text{ direction for joint } i \end{cases}$$

Coulomb friction terms for joint *i* are given by:

$$F_{Ci} = \begin{cases} f_{ci-} & \text{for angular motion in the } -q_i \text{ direction for joint } i \\ f_{ci+} & \text{for angular motion in the } +q_i \text{ direction for joint } i \end{cases}$$

for i = 2 and 3

and they are identified as :

$$\begin{bmatrix} f_{v2-} \\ f_{v2+} \\ f_{v3-} \\ f_{v3+} \end{bmatrix} = \begin{bmatrix} 11.49036 \\ 10.9504 \\ 7.9495 \\ 8.5941 \end{bmatrix} \qquad \begin{bmatrix} f_{c2-} \\ f_{c2+} \\ f_{c3-} \\ f_{c3+} \end{bmatrix} = \begin{bmatrix} -7.2718 \\ 8.1348 \\ -4.2873 \\ 4.2454 \end{bmatrix}$$

The following initial conditions

$$q_2 = 0.5\ rad, \quad \dot{q}_2 = 0\ rad/\sec$$
$$q_3 = 1\ rad, \quad \dot{q}_3 = 0\ rad/\sec$$

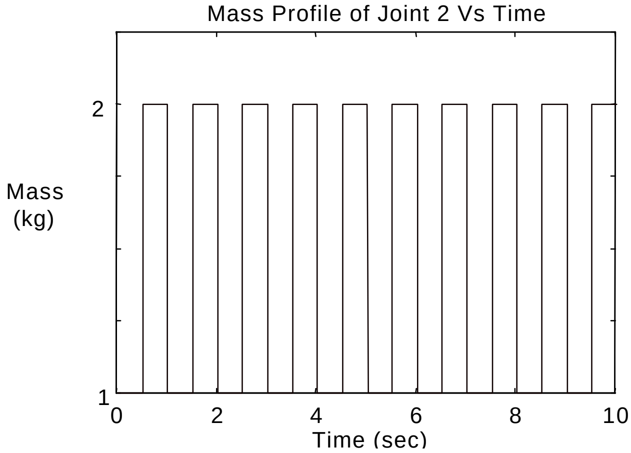
are chosen so as to cover a wider operating range for the fuzzy controller parameters which will be used as fuzzy linguistic information to be incorporated into the system to speed up adaptation.

The desired trajectories having the following sinusoidal form are used for Joints 2 and 3 respectively:

$$\text{Joint } 2: \quad q_{2d} = 30^{\circ}(1-\cos(2pt))$$
$$\text{Joint } 3: \quad q_{3d} = 45^{\circ}(1-\cos(2pt))$$

In order to compare the proposed IAFC with Slotine and Li's method, we introduce payload variations as shown in Figure 5.2 and an external disturbance given by the following equation:

$$t_d = 100\sin(2pt)$$



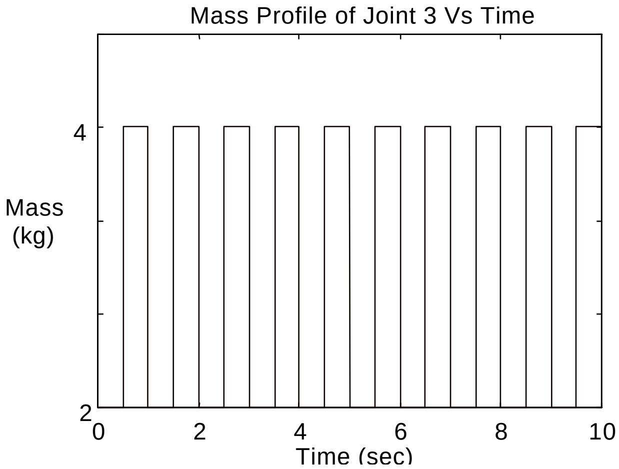


Figure 4.2 : Mass profiles used in the simulation for the two-link SCARA robot

Using the dynamic model of the TT-3000 SCARA as a two-link arm, the proposed IAFC is used to track the desired trajectory. The adaptive gains are found to be:

$$K_p = \begin{bmatrix} 500 & 0 \\ 0 & 500 \end{bmatrix} \qquad K_v = \begin{bmatrix} 45 & 0 \\ 0 & 45 \end{bmatrix} \qquad Q = \begin{bmatrix} 2000 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 2000 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\gamma_1 = \gamma_2 = 5 \qquad a_1 = a_2 = 5$$

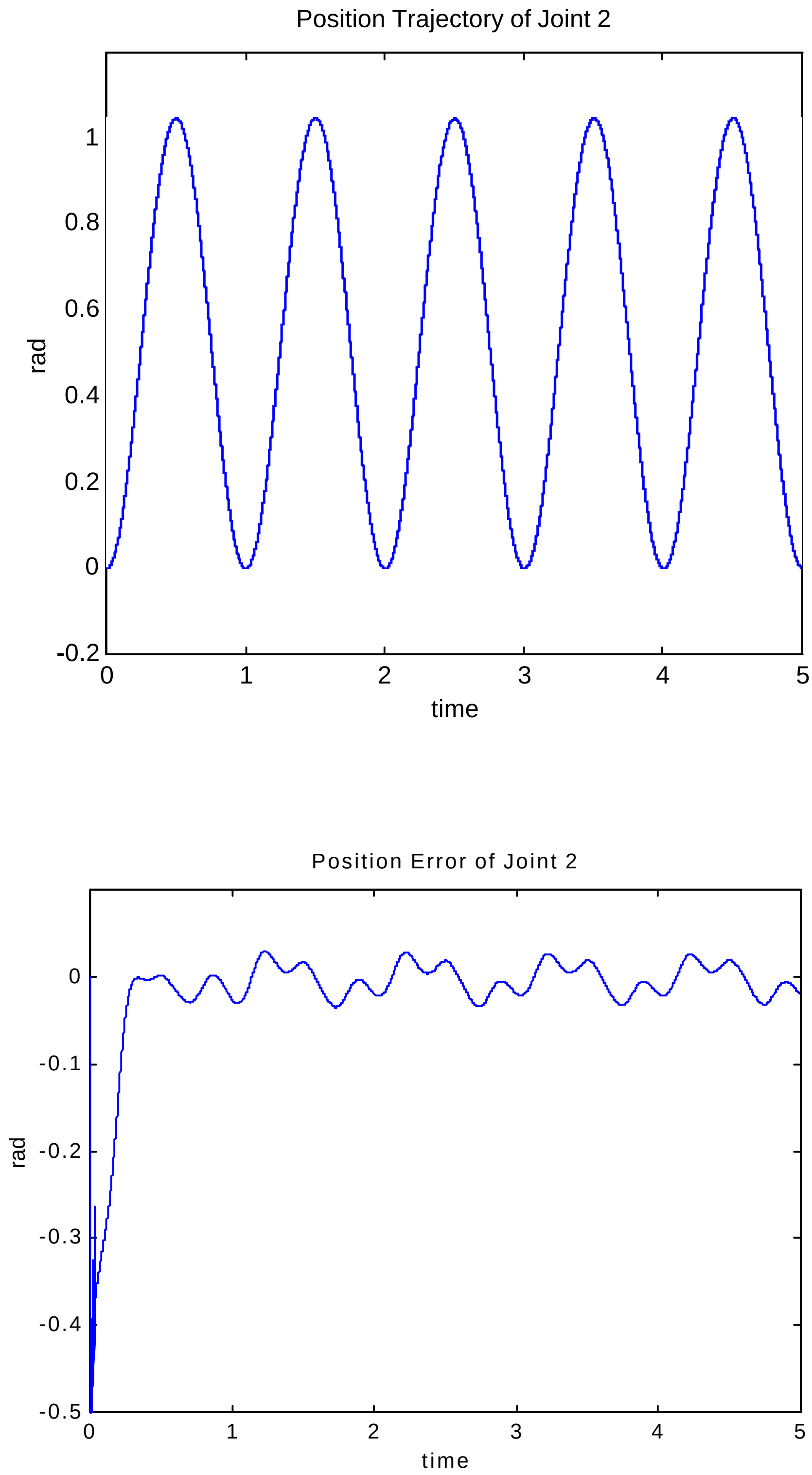
3.3 Results and Discussions

Figure 4.3 shows the position tracking trajectories and the corresponding position tracking errors for joint 2 using the Slotine and Li's method. Figure 4.4 depicts those of joint 3. Desired position trajectories are indicated in dashed lines and actual trajectories employing the Slotine and Li's method are indicated in solid lines. Figure 4.5 shows the corresponding control torques.

Figure 4.6 shows the position tracking trajectories and the corresponding position tracking errors for joint 2 using the IAFC. Figure 4.7 depicts those of joint 3. Again, desired position trajectories are indicated in dashed lines and actual trajectories after incorporating fuzzy descriptions using the IAFC are indicated in solid lines. Figure 4.8 shows the corresponding control torques.

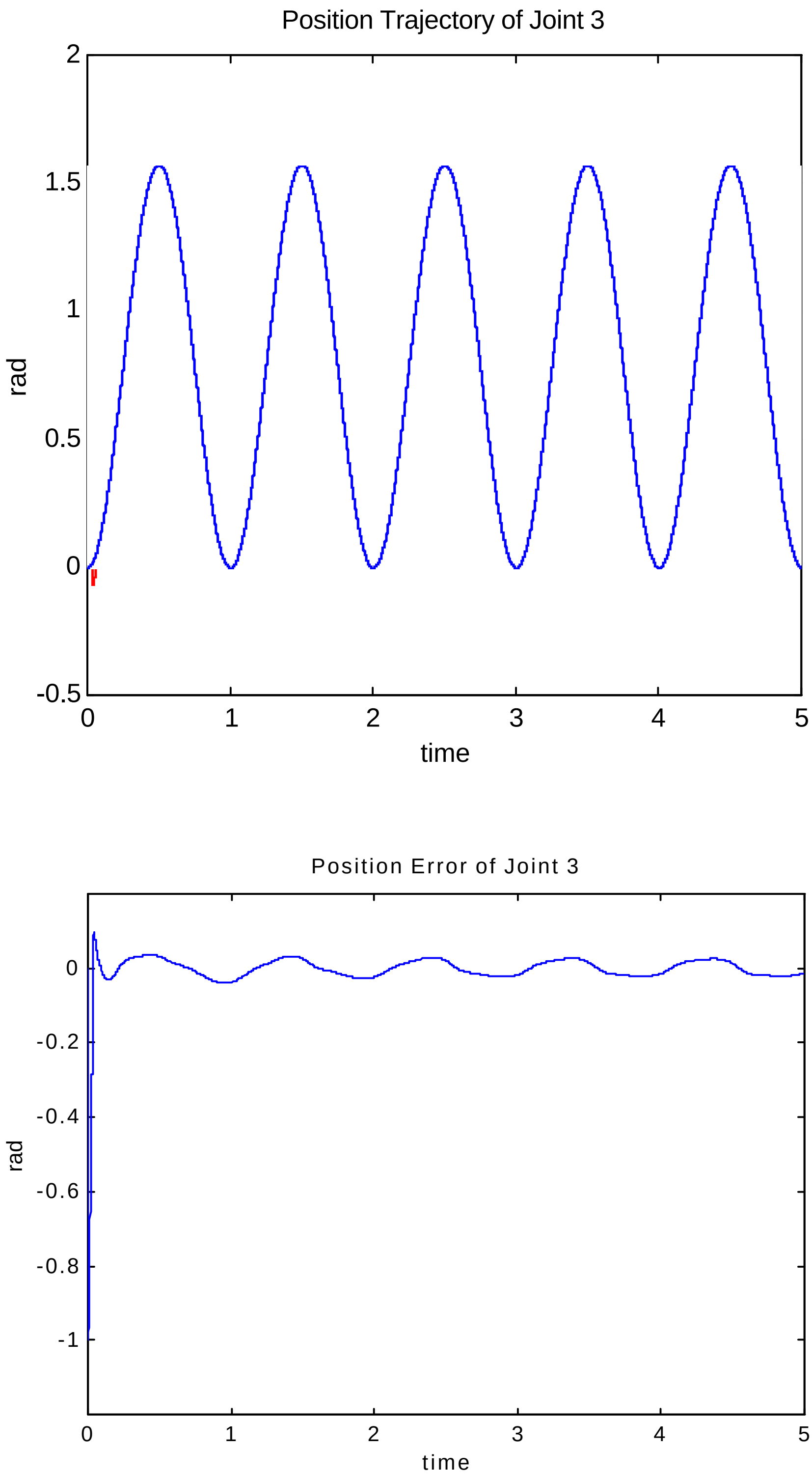
Comparing Figures 4.3 and 4.6, we observed that the transient response had improved after fuzzy descriptions had been incorporated. Furthermore, the steady-state errors and the magnitude of the control torque have been significantly reduced after using IAFC.

The primary reason IAFC could outperform the Slotine and Li's method is that the latter is based on the exact mathematical model of the Seiko SCARA robot. When the robot undergoes the pick and place operation, the mathematical model based upon which the controller was designed in Slotine and Li's method becomes invalid. However, using the proposed IAFC, human experiences have been incorporated in the form of linguistic fuzzy information to deal with changes in the mathematical model. Hence, despite that the mathematical model is no longer accurate as a result of the pick and place operation, the IAFC is able to handle the uncertainties and outperform the Slotine and Li's method.



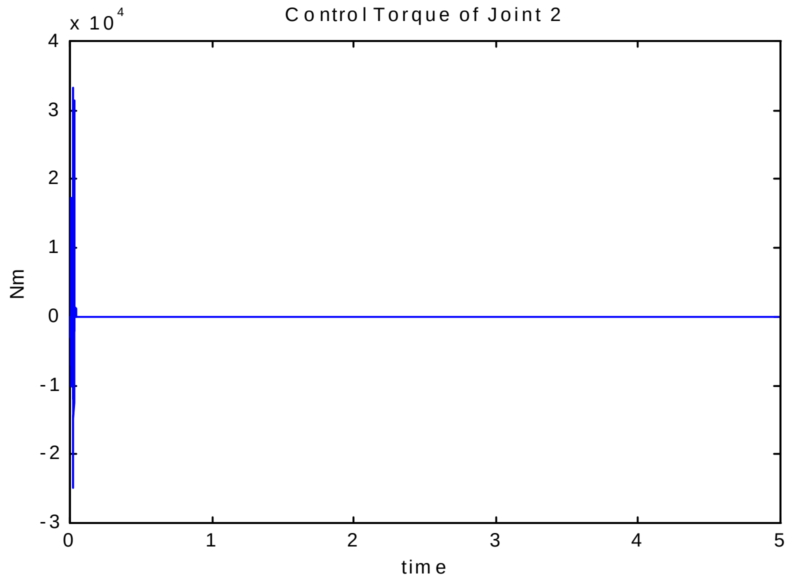
Slotine and Li's method Desired trajectory

Figure 4.3 : Position trajectories and position tracking errors at joint 2 (T1-Axis) of the SCARA robot using Slotine and Li's method



Slotine and Li's method ——— Desired trajectory - - - - - - -

Figure 4.4 : Position trajectories and position tracking errors at joint 3 (T2-Axis) of the SCARA robot using Slotine and Li's method



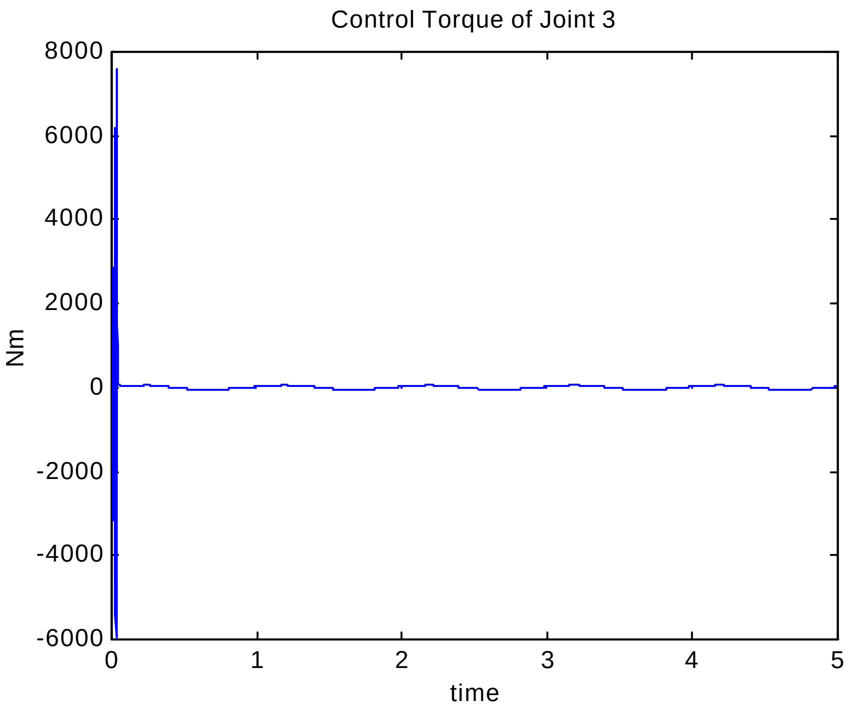


Figure 4.5 : Control torque of the SCARA robot using Slotine and Li’s method

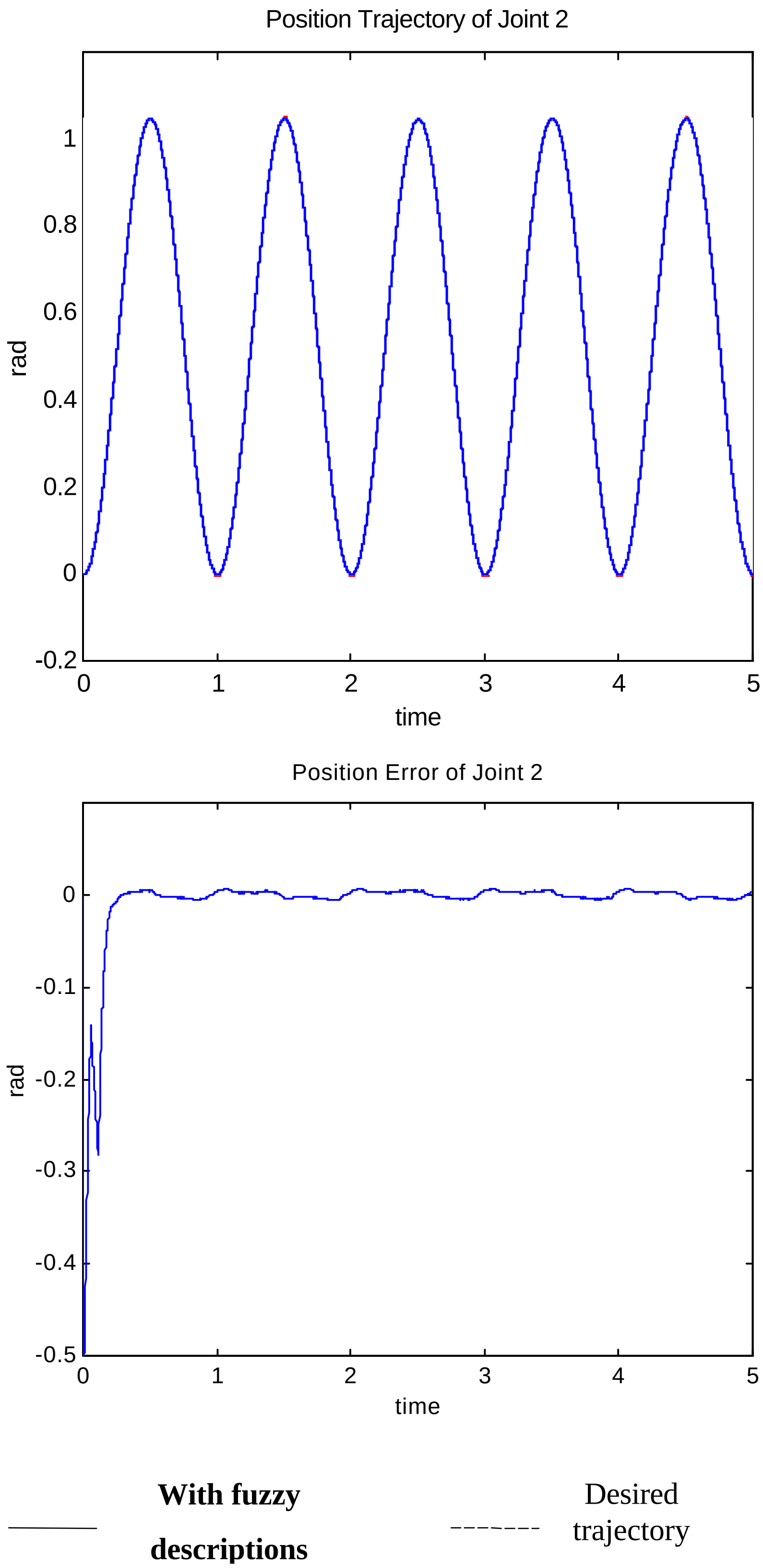
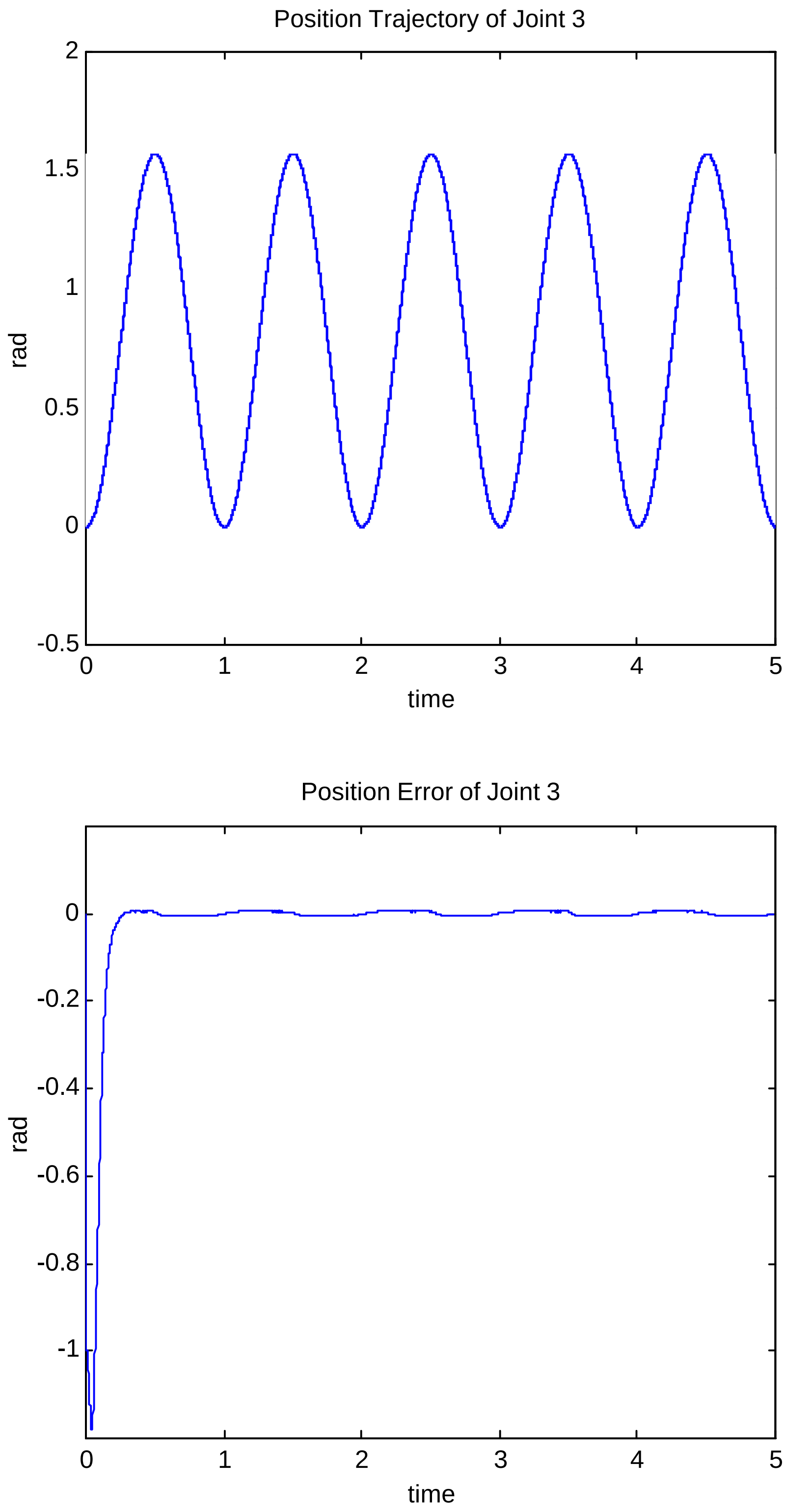
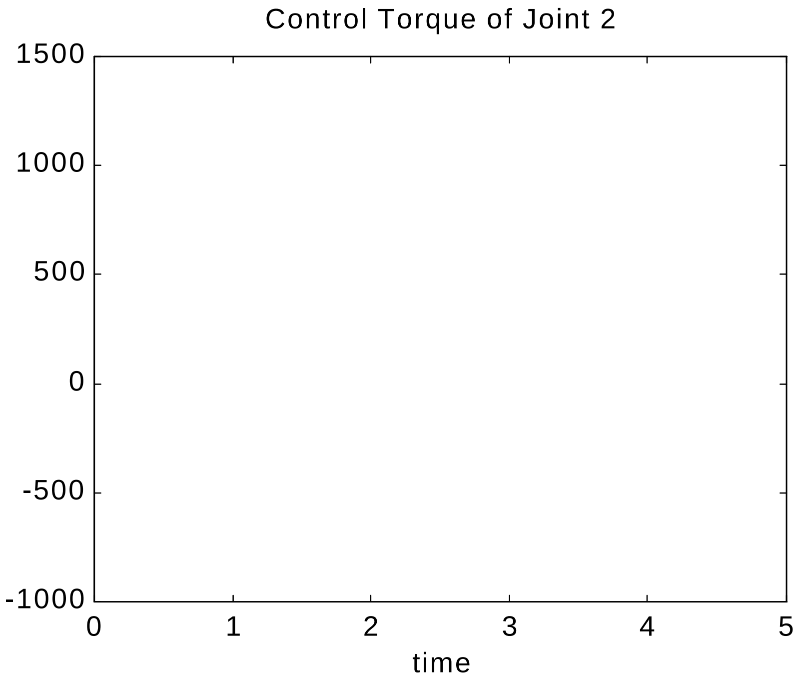


Figure 4.6 : Position trajectories and position tracking errors at joint 2 (T1-Axis) of the SCARA robot using IAFC



With fuzzy descriptions ——— Desired trajectory -------

Figure 4.7 : Position trajectories and position tracking errors at joint 3 (T2-Axis) of the SCARA robot using IAFC



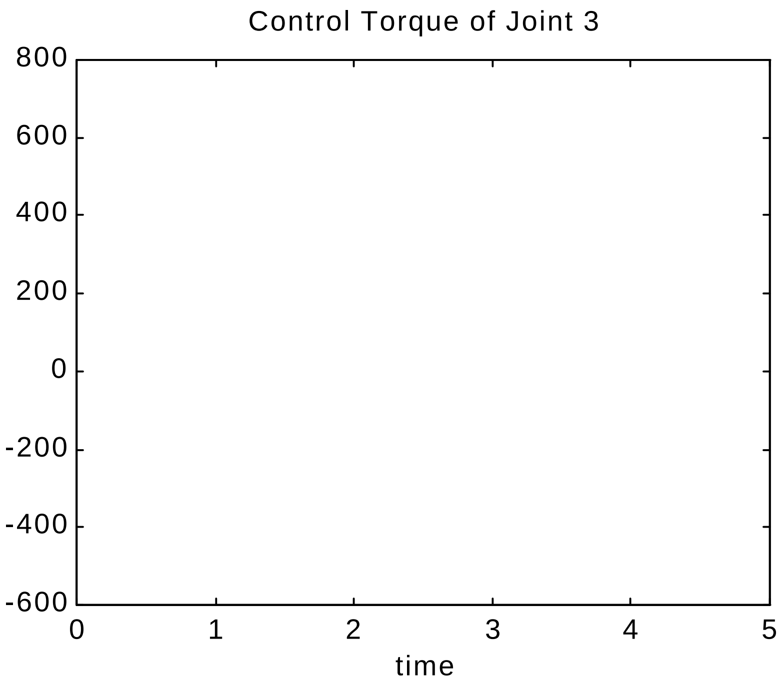


Figure 4.8 : Control torque of the SCARA robot using IAFC

3.4 Summary

In general, the IAFC is able to obtain good tracking performance after initial adaptation. By incorporating fuzzy information into the system, performance can be enhanced significantly even when there are mass variations and external disturbance introduced. From the above derivation and simulation results obtained, it is evident that the proposed IAFC is stable and robust and can track any desired trajectories. Furthermore, it does not require the exact mathematical model of the robot under control, thanks to the capability of incorporating fuzzy information to speed up adaptation.

4. Conclusions

In this paper, we have developed an Indirect Adaptive Fuzzy Controller (IAFC) which does not require an accurate mathematical model of the robot dynamics. The controller guarantees the global stability of the resulting closed-loop system in the sense that all the signals are bounded. The IAFC is employed to control an industrial SCARA robot to track a sine-wave trajectory with time-varying mass profile. Simulation results show that the IAFC could perform successful tracking after initial adaptation and it outperforms the algorithm of Slotine and Li’ s method.

Appendix : Proof of Lemma 1

Substituting Eq. (3.12) into Eq. (3.2), after some manipulations, the error dynamics becomes

$$\dot{X} = AX + B\left[\left(\hat{F}(\theta,\dot{\theta}/\phi) - F(\theta,\dot{\theta})\right) + \left(\hat{G}(\theta/\phi) - G(\theta)\right)\tau_c - G(\theta)\tau_s\right] \qquad \text{(A.1)}$$

and we have

$$\begin{aligned}\dot{V}_e &= -\frac{1}{2}X^TQX + X^TPB\left[\left(\hat{F}(\theta,\dot{\theta}/\phi) - F(\theta,\dot{\theta})\right) + \left(\hat{G}(\theta/\phi) - G(\theta)\right)\tau_c - G(\theta)\tau_s\right] \\ &\leq -\frac{1}{2}X^TQX + |X^TPB|\left[\left(|\hat{F}(\theta,\dot{\theta}/\phi)| + |F(\theta,\dot{\theta})|\right) + \left(|\hat{G}(\theta/\phi)\tau_c| + |G(\theta)\tau_c|\right)\right] \\ &\qquad -X^TPBG(\theta)\tau_s \end{aligned} \qquad \text{(A.2)}$$

By knowing the bounds of $F(\theta,\dot{\theta})$ and $G(\theta)$, we can design a supervisory control law, τ_s such that the right hand side of Eq. (A.2) is nonpositive.

We can determine the bound functions $F^u(\theta,\dot{\theta})$, $G^u(\theta)$ and $G_l(\theta)$ such that $|F(\theta,\dot{\theta})| \leq F^u(\theta,\dot{\theta})$ and $G_l(\theta) \leq G(\theta) \leq G^u(\theta)$ for $\theta \in \Re^n$, where $F^u(\theta,\dot{\theta}) < \infty$, $G^u(\theta) < \infty$ and $G_l(\theta) > 0$ for $\theta \in \Re^n$.

Writing $\qquad t_s(q) = \left[t_{s1}(q) \quad t_{s2}(q) \quad \cdots \quad t_{sn}(q)\right]^T$

and $\qquad G_{li}^{-1}(q) = \left[G_{l1}^{-1}(q) \quad G_{l2}^{-1}(q) \quad \cdots \quad G_{ln}^{-1}(q)\right]^T$,

the *i*th row of $t_s(q)$, $t_{si}(q)$ is chosen as

$$t_{si}(q) = I^* \operatorname{sgn}(X^TPB_i)G_{li}^{-1}(q)\left[|\hat{F}(q,\dot{q}/f)| + F^u(q,\dot{q}) + |\hat{G}(q/f)t_c| + |G^u(q)t_c|\right] \qquad \text{(A.3)}$$

where $\qquad \operatorname{sgn}(X^TPB_i) = 1(-1) \quad if \quad X^TPB_i \geq 0\ (<0)$, $\quad$ for $i = 1, 2, \ldots n$

and $\qquad I^* = \begin{cases} 1, & V_e > \overline{V} \\ 0, & otherwise \end{cases}$

Consider the case when $V_e > \overline{V}$, we have

$$\dot{V}_e \leq -\frac{1}{2}X^T QX + |X^T PB|\Big[\big(|\hat{F}(\theta,\dot{\theta}/\phi)| + |F(\theta,\dot{\theta})|\big) + \big(|\hat{G}(\theta/\phi)\tau_c| + |G(\theta)\tau_c|\big)$$

$$-G(\theta)G_l^{-1}(\theta/\phi)\big(|\hat{F}(\theta,\dot{\theta}/\phi)| + F^u(\theta,\dot{\theta}) + |\hat{G}(\theta/\phi)\tau_c| + |G^u(\theta)\tau_c|\big)\Big]$$

$$\leq -\frac{1}{2}X^T QX \leq 0 \tag{A.4}$$

This means that for a prescribed $\overline{V}$, we can always guarantee that $V_e \leq \overline{V} < \infty$. Since P is a positive definite matrix, the boundedness of V_e implies the boundedness of the error vector, X and the boundedness of the joint position vector, θ. Hence, the system is Bounded-Input-Bounded-Output (BIBO) stable.

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