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INVERSE DYNAMICS AND FUZZY REPETITIVE LEARNING FLEXIBLE ROBOT CONTROL

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Abstract: Tracking of a square trajectory 12.6 m x 12.6 m by a two-link flexible robot manipulator is performed repetitively for both inverse dynamics control (IDC) and fuzzy logic control (FLC). Repetitive learning inverse dynamics control (RLIDC) achieves no improvement in tracking but repetitive learning fuzzy logic control (RLFLC) achieves greater precision where cyclic tracking enables the fuzzy inference system to self-adapt and further reduce tracking errors. *Copyright ©2002 IFAC*

Keywords: Robotic Manipulators, Inverse Dynamics Control, Fuzzy Control, Learning Algorithms, Trajectories

1. INTRODUCTION

The strict requirement for minimal vibration and precision control of a two-link flexible robot manipulator in spacecraft operations is emphasized in previous work (Banerjee and Singhose, 1998; Green and Sasiadek, 2000a, b) for tracking a square trajectory. Banerjee and Singhose (1998) used an input shaped inverse kinematics technique while comparable results were obtained using various fuzzy control techniques (de Silva, 1995; Green and Sasiadek, 2000a, b). Green and Sasiadek (2000a, b) used two fuzzy controllers to substitute for the robot nonlinear dynamics equations and a single tracking cycle was obtained. In Banerjee and Singhose (1998) trajectory periodicity studies were included.

Repetitive control (RC) occurs when periodic signals input to the system and is a natural control problem encountered in many engineering applications including space robotics. A vast amount of literature exists on robot learning control of which iterative learning control (ILC) pioneered by Arimoto, *et al.* (1984), plays a significant part. Repetitive learning control (RLC) is ILC where initial states of the robot are not reset at the start of each iteration. Essentially RLC is a simple technique requiring less *a priori* knowledge of the controlled system and capable of modifying control input error signals automatically based on prior iterations. The aim is to track a trajectory as close as possible to that commanded by increasing the number of iterations. Principal works are (Goldsmith, 2000; Hara, Yamamoto, Omata and Nakano, 1988; Horowitz, 1993; Sison and Chong, 1996; Weiss, 1997; Yamamoto, 1993). Typically, they include adaptive algorithms that successively improve performance to achieve asymptotic zero error tracking based on the betterment learning laws proposed by Arimoto, *et al* (1984). FLC studies were conducted (Bonarini, 1994; Layne and Passino, 1992) on *learn behaviours* which include techniques to modify the relationship between inputs and outputs through control actions based on a reference model and reinforcement learning algorithms and, evolutionary learning techniques for populations of fuzzy rules (ELF) based on genetic algorithms.

In this paper, the result of previous work by Green and Sasiadek (2000a, b) is extended to demonstrate the effects of repeated learning. Trajectories obtained for five iterations, given in Figs. 6, 7, 8 and 9, show a distinct advantage of RLFLC over RLIDC.

2. FLEXIBLE ROBOT MANIPULATOR

The two-link flexible robot manipulator shown in Fig. 1 has a shoulder joint revolute 2π rad and an elbow joint oscillating ~3/2π rad. Robot motion and vibration modes are restricted to the x-y plane. Robot manipulator dynamics, physical constants and control parameters are those used in Banerjee and Singhose, (1998). The nonlinear robot dynamics equations are given in vector form as:

$$\mathbf{U} = \mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\dot{\mathbf{q}}, \mathbf{q}) \quad (1)$$

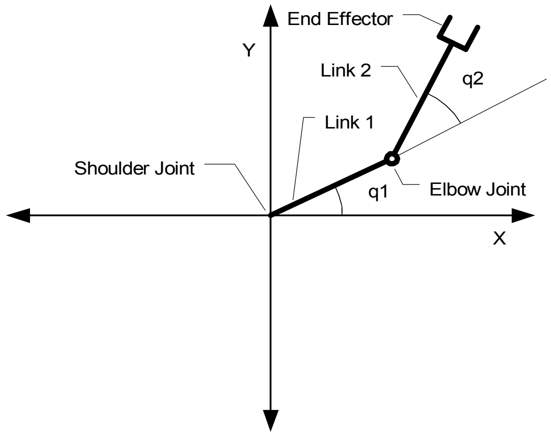


Fig. 1. Two-Link Flexible Robot Manipulator

$$\mathbf{M(q)} = \begin{bmatrix} mL^2(1.666+\cos q_2) & mL^2(0.333+0.5\cos q_2) \\ mL^2(0.333+0.5\cos q_2) & 0.333mL^2 \end{bmatrix}$$

$$\mathbf{C(\dot{q},q)} = -(0.5mL^2 \sin q_2)\left[\dot{q}_2(2\dot{q}_1+\dot{q}_2) \quad -\dot{q}_1\right]^{\mathrm{T}}$$

$\mathbf{U} = [u_1, u_2]^{\mathrm{T}} =$ torque vector control law
$L = L_1 = L_2 = 4.5$ meters = length of each link
$m = 1.5075$ kg
$q_i =$ slew angle, $i = 1, 2$
$\mathbf{q}$ = slew angles vector
$\mathbf{q}$ = slew angular velocities vector
$\zeta = 0.707$, closed-loop damping ratio
$\omega = 8.21$ Hz, first open-loop frequency mode

3. INVERSE DYNAMICS CONTROL

Fig. 2 shows a block diagram of the general control scheme and Figs. 3a & b, show details of an IDC loop for the two-link flexible manipulator. Common to both IDC and FLC schemes is the control law of the input torque vector given by Eqn. (2).

$$\mathbf{U} = \mathbf{J}^{\mathrm{T}}(\mathbf{q})\left[\mathbf{K}_{\mathrm{p}}\begin{bmatrix} e_x \\ e_y \end{bmatrix} + \mathbf{K}_{\mathrm{d}}\begin{bmatrix} \dot{e}_x \\ \dot{e}_y \end{bmatrix}\dot{\mathbf{q}}\right] \qquad (2)$$

$\mathbf{J(q)}$ = Jacobian of direct kinematics
$\mathbf{J}^{\mathrm{T}}\mathbf{(q)}$ = Jacobian transpose
$\mathbf{K}_{\mathrm{p}}$ = $\mathrm{diag}\left[\omega^2, \omega^2\right]$ = proportional gain
$\mathbf{K}_{\mathrm{d}}$ = $\mathrm{diag}\left[2\zeta\omega, 2\zeta\omega\right]$ = derivative gain
e_x, e_y = errors vector, i.e. $x_c - x$, $y_c - y$
$\dot{e}_x, \dot{e}_y$ = change of input errors vector
x_c, y_c = commanded end effector positions
x, y = actual end effector positions

$\mathbf{K}_{\mathrm{p}} = \mathrm{diag}\left[67.4, 67.4\right]$ and $\mathbf{K}_{\mathrm{d}} = \mathrm{diag}\left[11.61, 11.61\right]$ are calculated from the manipulator parameters. Commanded x_c, y_c positions are input from a Matlab™ matrix. The IDC scheme is typical for a robot and used in previous work (Green and Sasiadek, 2000a, b) while $\mathbf{K}_{\mathrm{p}}$ and $\mathbf{K}_{\mathrm{d}}$ are calculated from Banerjee and Singhose, (1998). Gravity and joint friction are neglected.

4. FUZZY CONTROL

The fuzzy control model shown in Fig. 5a utilizes the same servo parameters and control law as the IDC scheme to calculate torque but, two coupled fuzzy controllers substitute the nonlinear dynamics equations. Torque feeds to each FLC through normalizing gains where link 1 has a torque input, and link 2 has both acceleration and torque inputs shown in Figs. 5b & c. The fuzzy controllers have input and output variables each with nine Gaussian membership functions. Verbal descriptors Positive and Negative, High/Low, Very High/Low and Zero are denoted NVH, NH, NL, NVL, ZERO, PVL, PL, PH and PVH. Link 1 has nine fuzzy rules with torque universe of discourse -500 to 500 N-m. Link 2 has eighty-one fuzzy rules with acceleration and torque universes of discourse -2 to 2 rad/s^2 and -200 to 200 N-m respectively. Each link has acceleration output universe of discourse -5 to 5 rad/s^2. The torque input variable membership function (MF) universe of discourse shown in Fig. 4, is typical for all fuzzy variables in the Fuzzy Inference System (FIS).

Table 1 is the fuzzy rule base of the form:

IF **torque(1)** is NL THEN **acceleration(1)** is NL

IF **torque(1)** is PH THEN **acceleration(1)** is PH

Table 2 represents is the fuzzy rule base of the form:

IF **torque(2)** is PL and **acceleration(12)** is PL THEN **acceleration(2)** is PH

IF **torque(2)** is NVL and **acceleration(12)** is PVL THEN **acceleration(2)** is ZERO

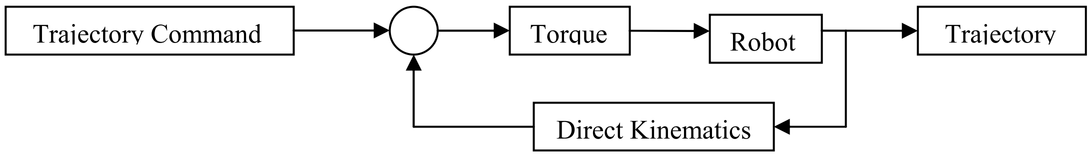


Fig. 2. Robot Manipulator Control Block Diagram

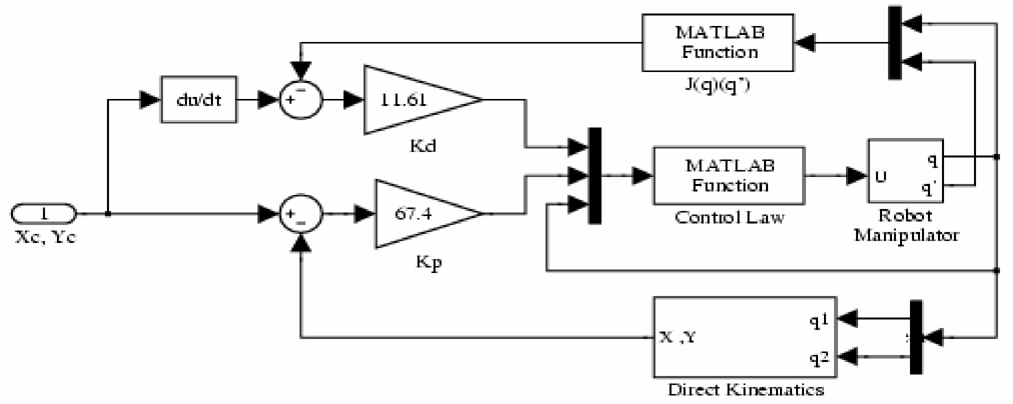


Fig. 3a. Inverse Dynamics Control Scheme

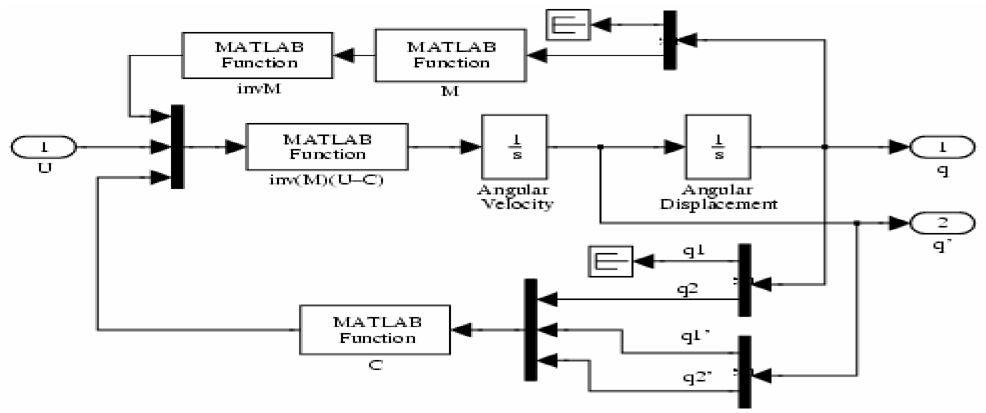
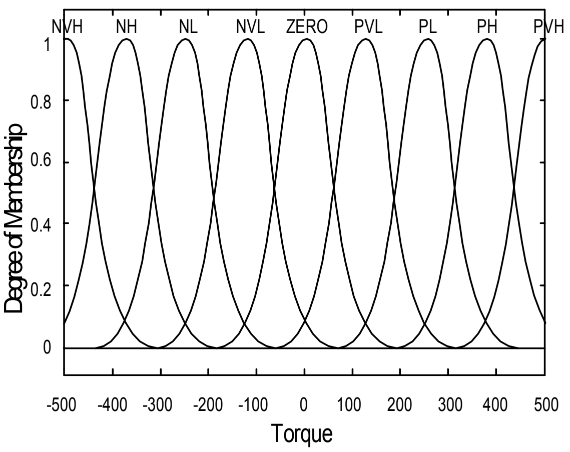


Fig. 3b. Inverse Dynamics Robot Manipulator



(N-m)

Fig. 4. Typical Input Membership Functions

Accelerations are fed through output scaling gains, K_1 and K_2, which modify the membership function base widths and dampen flexural vibrations to obtain the best square trajectory. Numerous simulations were performed with values of K_1 and K_2 initially low then increased until a final square trajectory emerged at values K_1=192000 and K_2=163954. Limits of stability constitute the ranges:

$$186405.8 <= K_1 <= 193500$$
$$163952.4 <= K_2 <= 163955.84$$

To ensure stability, K_1 and K_2 values were constant during all repetitive learning control simulations.

5. REPETITIVE LEARNING CONTROL

The repetitive control technique aims to train a robot on the premise that it must execute periodic motions, such that, its performance improves after each iteration and asymptotically tracks a desired trajectory. For ILC, resetting the robot back to initial states for each iteration demands a high degree of dexterity. For RLC there is a no-reset condition and

the control law is updated by previous iterations.
Many proposed ILC systems (Arimoto, 1984; Horowitz, 1993; Sison and Chong, 1996) typically update the control law Eqn. (2) with a proportional or derivative error term and learning gain, $\mathbf{K}_L$, for algorithms in the form of Eqns. (3) and (4).

Also, using the concept of repetitive effort control Goldsmith, (2000), derives an iterative control law, in which, $\mathbf{K}_L$ is substituted by a control operator $\mathbf{C}_L$ given as:

$$\mathbf{U}_L^i = \mathbf{U}_L^{i-1} + \mathbf{C}_L \begin{bmatrix} e_x \\ e_y \end{bmatrix}^i \qquad (5)$$

i = 1,2,3,……….n iterations

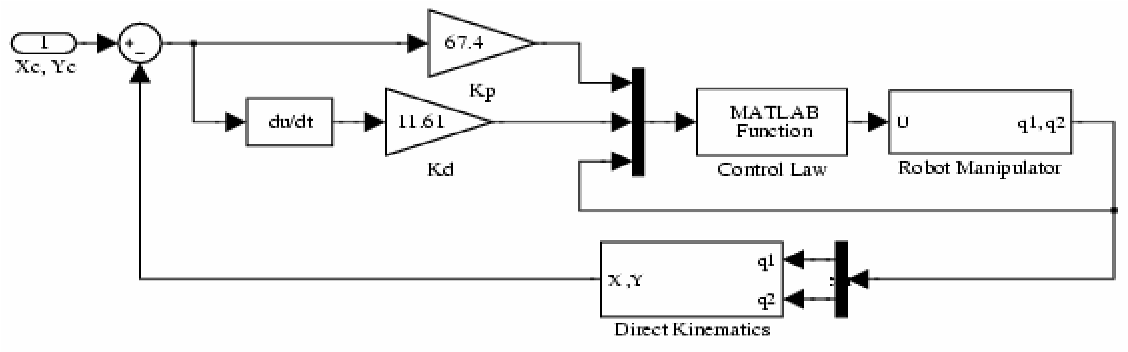


Fig. 4a. Fuzzy Control Scheme

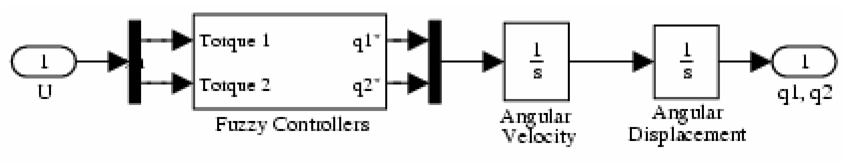


Fig. 4b. Fuzzy Robot Manipulator

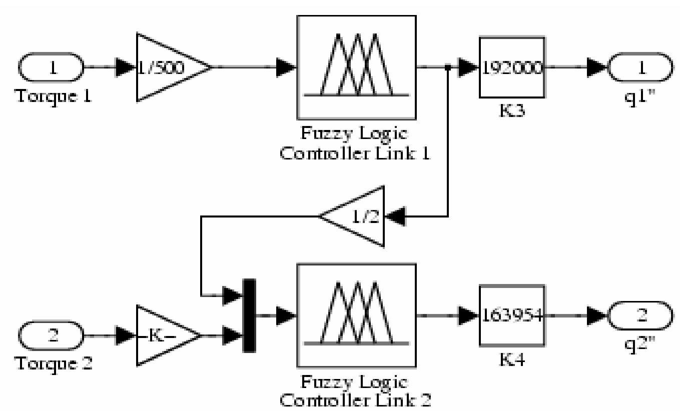


Fig. 4c. Fuzzy Controllers

$$\mathbf{U}_{k+1} = \mathbf{U}_k + \mathbf{K}_L \begin{bmatrix} e_x \\ e_y \end{bmatrix}^k \qquad (3)$$

or

$$\mathbf{U}_{k+1} = \mathbf{U}_k + \mathbf{K}_L \begin{bmatrix} \dot{e}_x \\ \dot{e}_y \end{bmatrix}^{k+1} \qquad (4)$$

k = 1,2,3,…….n iterations

In this study, the control law for both RLIDC and RLFLC is preserved with simple updates of position and velocity feedback errors given by.

$$\mathbf{U}_{k+1} = \mathbf{U}_k + \mathbf{J}^T(\mathbf{q}) \left(\mathbf{K}_p \begin{bmatrix} e_x \\ e_y \end{bmatrix} + \mathbf{K}_d \begin{bmatrix} \dot{e}_x \\ \dot{e}_y \end{bmatrix} \dot{\mathbf{q}} \right)^{k+1} \qquad (6)$$

k = 1,2,3,…….n iterations

Table 1 Rule Base for Link 1

Torque (1)	NVH	NH	NL	NVL	ZERO	PVL	PL	PH	PVH
Acceleration (1)	NVH	NH	NL	NVL	ZERO	PVL	PL	PH	PVH

Table 2 Rule Base for Link 2

	Torque (2)								
Acceleration (2) / Acceleration(12)	NVH	NH	NL	NVL	ZERO	PVL	PL	PH	PVH
NVH	NVH	NVH	NH	NH	NH	NL	NL	NVL	ZERO
NH	NVH	NH	NH	NH	NL	NL	NVL	ZERO	PVL
NL	NH	NH	NH	NL	NL	NVL	ZERO	PVL	PL
NVL	NH	NH	NL	NL	NVL	ZERO	PVL	PL	PL
ZERO	NH	NL	NVL	ZERO	ZERO	ZERO	PVL	PL	PH
PVL	NL	NL	NVL	ZERO	PVL	PL	PL	PH	PH
PL	NL	NVL	ZERO	PVL	PL	PL	PH	PH	PH
PH	NVL	ZERO	PVL	PL	PL	PH	PH	PH	PVH
PVH	ZERO	PVL	PL	PL	PH	PH	PH	PVH	PVH

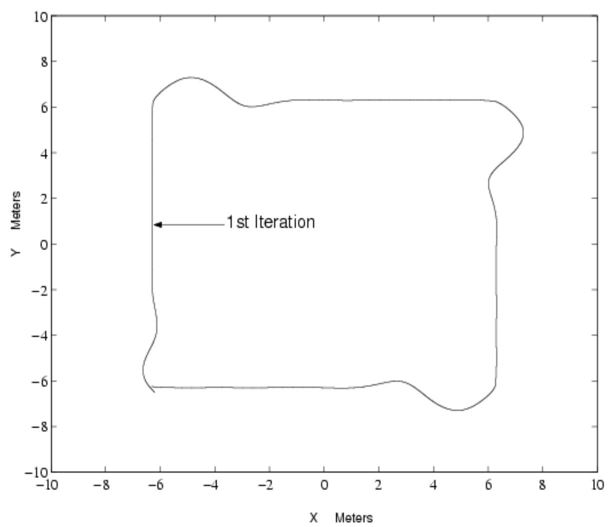


Fig. 6. RLIDC - 1st Iteration

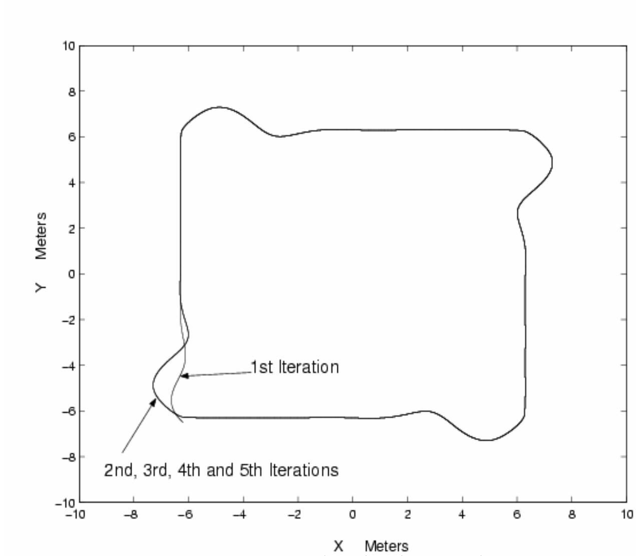


Fig. 8. RLIDC - 1st, 2nd, 3rd, 4th and 5th Iterations

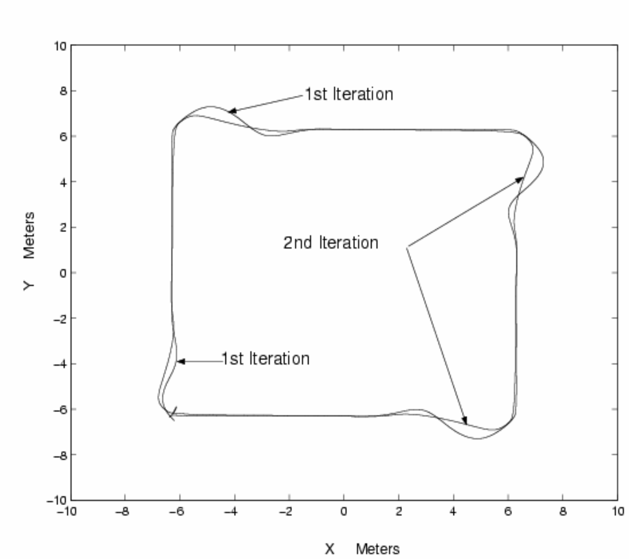


Fig. 7. RLIDC – 1st and 2nd Iterations

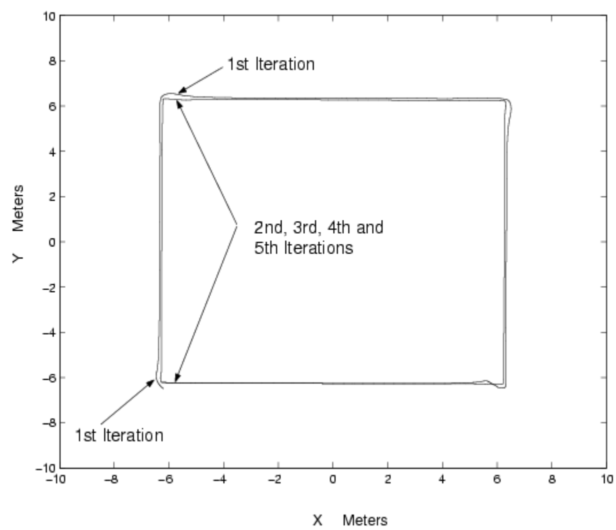


Fig. 9. RLFLC– 1st, 2nd, 3rd, 4th and 5th Iterations

For RLIDC, Figs. 6, 7 and 8 show very large amplitude transient vibrations at direction switches in the 1st iteration, followed by slight reduction in the 2nd iteration and then reverts back to the 1st iteration trajectory for all successive iterations, albeit stable. A large amplitude vibration occurs at the start point. In contrast, RLFLC trajectories, in Fig. 9, tracked after the 1st iteration shows a distinct improvement with only a very slight transient vibration at one switch. This improved performance is maintained for all subsequent iterations. On average, each RLIDC trajectory was tracked in 5 min 35 sec and each RLFLC trajectory tracked in 6 min 8 sec for the first, and 7 min 17 sec for subsequent iterations.

6. CONCLUSIONS

Previous work demonstrates the greater tracking precision obtained by substituting robot dynamics equations with FLCs over conventional control methods. Whereas, in this paper, the same FLC technique extends to repeated tracking without initial state reset and implementation of a complex fuzzy reference model design with a learning mechanism, i.e. fuzzy inverse model and fuzzy rule modifier. As only one set of fuzzy rules is used for each link, the ELF technique is not considered. When RLIDC is used without the application of an adaptive control algorithm, there is no improvement in tracking. In contrast the RLFLC trajectory converges close to that commanded after the first repeat cycle, thereby improving upon results obtained in previous work for a single tracking cycle. It has a demonstrated ability to self-adapt upon periodic tracking and asymptotically converge closer to a zero error trajectory without some estimated learning gain or modification of the rule base.

7. REFERENCES

Arimoto, S., S. Kawamura and F. Miyazaki (1984). Bettering Operation of Robots by Learning. *Journal of Robotic Systems*, **1**, 123-140.

Banerjee, A.K. and W. Singhose (1998). Command Shaping in Tracking Control of a Two-Link Flexible Robot. *AIAA Journal of Guidance, Dynamics and Control*, **21**, Engineering Note, 1012-1015.

Bonarini, A. (1994). Learning Behaviour Represented as Fuzzy Logic Controllers. In: *Proceedings of the 2nd European Congress on Intelligent Technologies and Soft Computing (EUFIT '94)*, pp. 710-715, ELITE Foundation, Aachen, Germany.

de Silva, C.W. (1995). *Intelligent Control: Fuzzy Logic Applications,* CRC Press.

Goldsmith, P. (2000). Repetitive Effort Control Applied to LTI Systems. In: *Proceedings of IASTED International Conference on Control and Applications*, No. 310-119, Cancun, Mexico.

Green, A. and J.Z. Sasiadek (2000a). Direct, Optimal, Stochastic and Fuzzy Control of a Two-Link Flexible Manipulator. In: *Proceedings of the AIAA Guidance, Navigation and Control Conference and Exhibit*, No. A00-37130, Denver, Colorado.

Green, A. and J.Z. Sasiadek (2000b). Direct and Fuzzy Tracking Control of a Two-Link Flexible Manipulator. In: *Proceedings of the 6th International IFAC Symposium on Robot Control, SYROCO '00*, Vol. 1, pp. 555-560, Vienna, Austria.

Hara, S., Y. Yamamoto, T. Omata and M. Nakano (1988). Repetitive Control System: A New Type Servo System for Periodic Exogenous Signals, *IEEE Transactions on Automatic Control*, **33**, 659-668.

Horowitz, R. (1993). Learning Control of Robot Manipulators. *ASME Journal of Dynamic Systems, Measurement and Control*, **115**, 402-411.

Layne, J.R. and K.M. Passino (1992). Fuzzy Model Reference Learning Control. In: *Proceedings of the 1st IEEE Conference on Control Applications*, pp. 686-691, Dayton, Ohio.

Sison, L.G. and E.K.P. Chong (1996). No-Reset Iterative Learning Control. In: *Proceedings of the 35th IEEE Conference on Decision and Control*, pp. 3062-3063, Kobe, Japan.

Weiss, G. (1997). Repetitive Control Systems: Old and New Ideas. In: *Systems and Control in the Twenty-First Century*, (C. Byrnes, B. Datta, D. Gilliam and C. Martin, Ed.), pp. 389-404, Birkhäuser, Basel.

Yamamoto, Y. (1993). Learning Control and Related Problems in Infinite-Dimensional Systems. In: *Essays on Control: Perspectives in the Theory and its Applications*, (H.L.Trentelman and J.C. Willems, Ed.), pp. 191-222, Birkhäuser, Boston.