International Journal of Electrical and Computer Engineering (IJECE)
Vol.2, No.1, February 2012, pp. 90~97
ISSN: 2088-8708

Adaptive Neuro-fuzzy Inference System Based Control of Puma 600 Robot Manipulator

Ouamri Bachir*, Ahmed-foitih Zoubir**
*Département de technologie, Université de Bechar
** Département d'électronique, Université des sciences et de la technologie d'Oran

Article Info

Article history:

Received Oct 19th, 2011
Revised Jan 21th, 2012
Accepted Feb 10th, 2012

Keyword:

Fuzzy computed torque control
Robot control
Adaptive neuro-fuzzy inference system (ANFIS).

ABSTRACT

The strong dependence of the computed torque control of dynamic model of the robot manipulator makes this one very sensitive to uncertainties of modelling and to the external disturbances. In general, the vector of Coriolis torque, centrifugal and gravity is very complicated, consequently, very difficult to modelled. Fuzzy Logic Controller can very well describe the desired system behavior with simple "if-then" relations owing the designer to derive "if-then" rules manually by trial and error. On the other hand, Neural Networks perform function approximation of a system but cannot interpret the solution obtained neither check if its solution is plausible. The two approaches are complementary. Combining them, Neural Networks will allow learning capability while Fuzzy-Logic will bring knowledge representation (Neuro-Fuzzy). This paper presents the control of puma 600 robot arm using Adaptive Neuro Fuzzy Inference System (ANFIS) based computed torque controller (type PD). Numerical simulation using the dynamic model of puma 600 robot arm shows the effectiveness of the approach in improving the computed torque method. Comparative evaluation with Fuzzy computed torque (type PD) control is presented to validate the controller design. The results presented emphasize that a satisfactory trajectory tracking precision and stabilility could be achieved using ANFIS controller than Fuzzy controller.

Corresponding Author:

Ouamri Bachir,
Département de technologie, Faculté des sciences et de technologie,
Université de Bechar,
Bp 417, Bechar 08000, Algeria.
Email: ouamribac@gmail.com

1. INTRODUCTION

The control of robot manipulators presents nowadays a major concern of research in robotics. Indeed the majorities of the tasks entrusted to the robots are delicate and require great precision in the fast trajectories. The use of the control by nonlinear decoupling constitutes a good approach in this direction. Such control is also known as dynamic control or computed torque because it is based on the use of dynamic model of the robot [1].

Implementing this controller requires knowledge accurate and complete model of the robot. In such a situation, this control is perfect. However, in practice this requirement is very difficult to satisfy considering the external disturbances acting on the robot. Under such conditions, this control technique is very sensitive and inefficient [2].

These drawbacks of the linearization control have motivated researchers to develop new versions and strategies of intelligent and adaptive control to limit their effects and to regain the effectiveness of this method [3]-[4], [10].

The FIS forms are a useful computing framework based on the concepts of fuzzy set theory, fuzzy if–then rules and fuzzy reasoning. The ANFIS [5]-[6] is a FIS implemented in the framework of an adaptive fuzzy neural network. It combines the explicit knowledge representation of a FIS with the learning power of ANNs. Usually, the transformation of human knowledge into a fuzzy system (in the form of rules and membership functions) does not give the target response accurately. So, the parameters of the FIS should be determined optimally.

In this paper, an Adaptive Neuro Fuzzy Inference System (ANFIS) based Computed Torque (*PD*) controller is applied to the dynamic model of puma 600 robot arm presented.

To validate the performance, a comparison with the fuzzy controller is performed under same tuning. The simulation results showed that the neuro-fuzzy technique present good results and that this controller is efficient and robust.

2. MODEL MOTION OF ROBOT MANIPULATOR

A robot manipulator consists of a mechanical structure, usually a set of rigid bodies connected in series by joints, with an end on the ground, which is the base of the robot, and the end body or effector.

The model of motion (or dynamics) of such a mechanism is usually described by the following matrix equation:

$$\Gamma = M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + F(\dot{q}) \tag{1}$$

Where Γ is the $n \times 1$ vector of actuator joint torque, $M(q)$ is the $n \times n$ symmetric positive-definite inertia matrix, $C(q,\dot{q})\dot{q}$ is the $n \times 1$ vector of Coriolis and centrifugal torque, $G(q)$) is the $n \times 1$ vector of gravitational torques, $q, \dot{q}, \ddot{q}$ are the joint displacement, velocity, and acceleration vectors, $F(\dot{q})$ is the $n \times 1$ vector of actuator joint friction forces, and n corresponds to the number of degrees of freedom of the robot.

We pose in the following:

$e = \tilde{q} = q_d - q$: Vector of the position error,

$\dot{e} = \dot{\tilde{q}} = \dot{q}_d - \dot{q}$: Vector of the velocity error,

$\ddot{e} = \ddot{\tilde{q}} = \ddot{q}_d - \ddot{q}$: Vector of the acceleration error.

Where q_d, $\dot{q}_d$ and $\ddot{q}_d$ are respectively the vectors of desired position, desired velocity and desired acceleration.

To ensure the linearization and the decoupling of the nonlinear system describes by the equation (1) in closed loop, we introduce a linearization control (computed torque) based on exact knowledge of the robot model and its implementation allows us direct. The loop of the linearization is achieved by choosing a torque Γ applied to the robot, as follows:

$$\Gamma = M(q)\Gamma_0 + C(q,\dot{q})\dot{q} + G(q) + F(\dot{q}) \tag{2}$$

Substituting Γ in expression (1) and taking into account $M(q)$ that is a regular matrix, we have n decoupled linear systems:

$$\ddot{q} = \Gamma_0 \tag{3}$$

Where Γ_0 is an auxiliary input of the select controller. A proportional derivative control (*PD*) is a typical choice for Γ_0, given by the equation:

$$\Gamma_0 = \ddot{q}_d + K_v(\dot{q}_d - \dot{q}) + K_p(q_d - q) \tag{4}$$

By the replacement of (4) in (3), we get the following error equation:

$$\ddot{e}+K_v\dot{e}+K_p e=0 \quad (5)$$

The error equation (5) is a linear differential equation of second order.
Where K_p and K_v are positive definite diagonal matrices, so the closed loop system becomes linear decoupled.

This equation has solution for an error $e(t)$ that exponentially tends to zero. The closed-loop system with this controller, where the model of the robot is known with accuracy, is asymptotically stable. In the case of an imprecise knowledge of parameters of the robot and/or presence of some unmodelled dynamics, the computed torque control shows its limits.

The solution we propose is to use ANFIS controller whose role is adjust, in permanent, the parameter K_p and K_v to compensate for neglected parts of the dynamic model.

The overall block diagram of the system under control is shown in Figure 1.

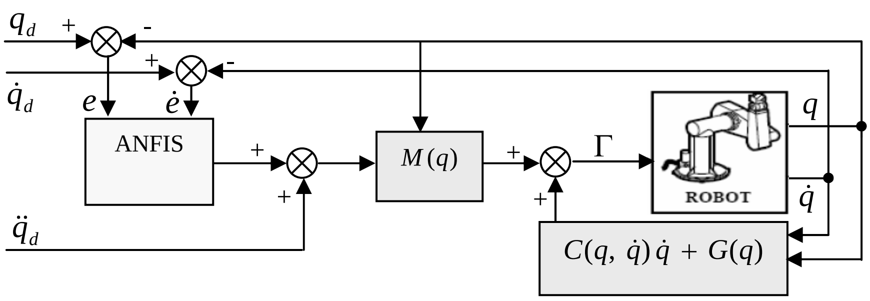


Figure 1. The overall block diagram of the system

3. ADAPTIVE NEURO FUZZY INFERENCE SYSTEME CONTROL

3.1. ANFIS architecture

A typical architecture of an ANFIS is shown in Figure 2, in which a circle indicates a fixed node, whereas a square indicates an adaptive node. For simplicity, we assume that the inference system under consideration has two inputs m, n and one output z. Among many FIS models, the Sugeno fuzzy model is the most widely applied one for its high interpretability and computational efficiency, and built-in optimal and adaptive techniques. For a first order Sugeno fuzzy model, a typical rule set with two fuzzy if / then rules can be expressed as:

Rule 1: if m is A_1 and n is B_1, then $z_1 = p_1 m + q_1 n + r_1$ (6)

Rule 2: if m is A_2 and n is B_2, then $z_2 = p_2 m + q_2 n + r_2$ (7)

where A_i and B_i are the fuzzy sets in the antecedent, and p_i, q_i and r_i are the design parameters that are determined during the training process. As in Figure1, the ANFIS consists of five layers:

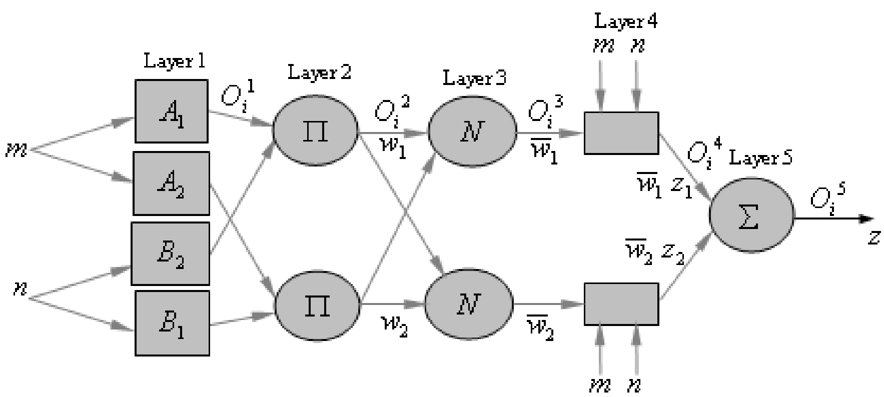


Figure 2. ANFIS Architecture

Layer 1: Every node i in the first layer employs a node function given by:

$$\begin{cases} O_i^1 = \mu_{A_i}(x), \quad i = 1, 2 \\ O_i^1 = \mu_{B_i}(x), \quad i = 1, 2 \end{cases} \tag{8}$$

where μ_{A_i} and μ_{B_i} can adopt any fuzzy membership function (MF).

Layer 2: Every node in this layer calculates the firing strength of a rule via multiplication

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1, 2 \tag{9}$$

Layer 3: The *i*-th node in this layer calculates the ratio of the *i*-th rule's firing strength to the sum of all rules firing strengths:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2. \tag{10}$$

where $\overline{w}_i$ is referred to as the normalized firing strengths.

Layer 4: In this layer, every node i has the following function:

$$O_i^4 = \overline{w}_i \, z_i = \overline{w}_i \, (p_i \, x + q_i \, y + r_i), \quad i = 1, 2 \tag{11}$$

where $\overline{w}_i$ is the output of layer 3, and (p_i, q_i, r_i) is the parameter set. The parameters in this layer are referred to as the consequent parameters.

Layer 5: The single node in this layer computes the overall output as the summation of all incoming signals, which is expressed as:

$$O_i^5 = \sum_i \overline{w} \, z_i = \frac{\sum_{i=1}^{2} w_i \, z_i}{\sum_{i=1}^{2} w_i}, \quad i = 1, 2 \tag{12}$$

The output z in Figure 1 can be rewritten as [7]-[9]:

$$z = (\overline{w}_1 \, x) \, p_1 + (\overline{w}_1 \, y) \, q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 \, x) \, p_2 + (\overline{w}_2 \, y) \, q_2 + (\overline{w}_2) r_2 \tag{13}$$

The ANFIS distinguishes itself from normal fuzzy logic systems by the adaptive parameters, i.e., both the premise and consequent parameters are adjustable. The most remarkable feature of the ANFIS is its hybrid learning algorithm. The adaptation process of the parameters of the ANFIS is divided into two steps. For the first step of the consequent parameters training, the Least Squares method (LS) is used, because the output of the ANFIS is a linear combination of the consequent parameters. The premise parameters are fixed at this step. After the consequent parameters have been adjusted, the approximation error is back-propagated (BP) through every layer to update the premise parameters as the second step. This part of the adaptation procedure is based on the gradient descent principle, which is the same as in the training of the BP neural network. The consequence parameters identified by the LS method are optimal in the sense of least squares under the condition that the premise parameters are fixed.

3.2. Adaptive neuro-fuzzy controller

In order to keep the robot, in joint space, a desired trajectory and its successive derivatives and , which describe respectively the desired velocity and desired acceleration, the strategy of the ANFIS control consists to adjust in permanent the values of the corrector gains. The neuro-fuzzy controller developed consists on two inputs, error (e) and change of error ($de = \dot{e}$) defined as:

$$\begin{cases} e = q_d - q \\ de = \dot{q}_d - \dot{q} \end{cases} \qquad (14)$$

This paper considers the ANFIS structure with first order Sugeno model containing 64 rules. Triangular membership functions with product inference rule are used at the fuzzification level. Hybrid learning algorithm that combines least square method with gradient descent method is used to adjust the parameter of membership function.

Structure of ANFIS used is shown in Figure 3.

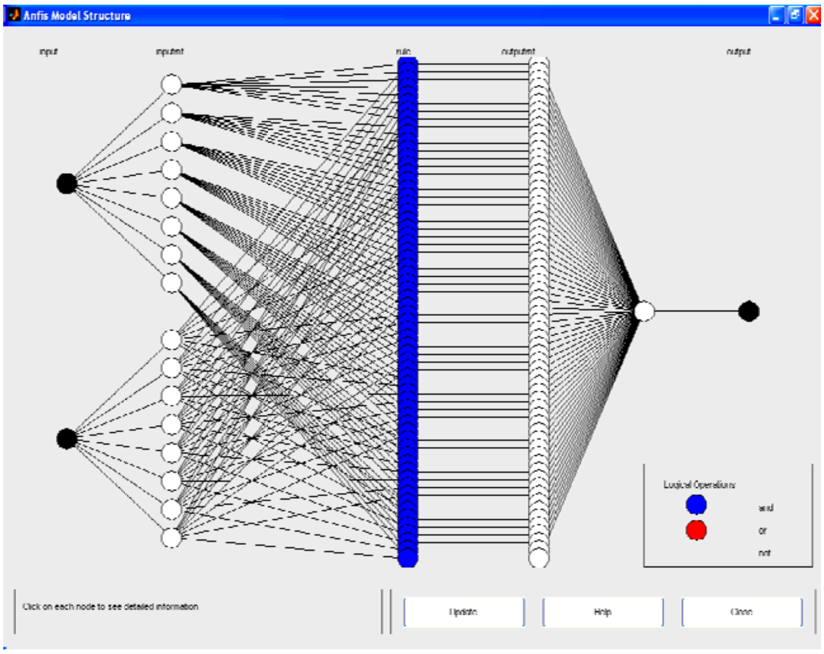


Figure 3. Structure of ANFIS

4. SIMULATION RESULTS

To show the contribution of the control by ANFIS and its improvements compared to the fuzzy logic method, a simulation was approved on a model of a robot manipulator puma 600, for the first three degrees of freedom, whose parameters are presented on table 1 [11]:

Table 1. Parameters of the Puma 600 robot manipulator used in simulation

Parameters	Values
Mass of the first body m_1	10,521 Kg
Mass of the second body m_2	10,236 Kg
Mass of the third body m_3	8,767 Kg
Coefficient of viscous friction f_1 of the 1st body	2,52 $N.m.s/rd$
Coefficient of viscous friction f_2 of the 2nd body	7 $N.m.s/rd$
Coefficient of viscous friction f_3 of the 3rd body	1,75 $N.m.s/rd$
Coefficient of dry friction f_4 of the 1st body	3,6 $N.m.s/rd$
Coefficient of dry friction f_5 of the 2nd body	10 $N.m.s/rd$
Coefficient of dry friction f_6 of the 3rd body	2,5 $N.m.s/rd$
Length of the first body $l_1 = r_2$	0,149 m
Length of the second body $l_2 = d_3$	0,432 m
Length of the third body $l_3 = a$	0,431 m

We considered a reference trajectory, ensuring continuity in position, velocity and acceleration, given by:

$$\begin{cases} q_{d1} = 3 + 6(\sin t + \sin 2t) \\ q_{d2} = 2 + 4(\cos t + \sin 2t) \\ q_{d3} = 4 + 5(\sin t + \cos 2t) \end{cases}$$

For the fuzzy controller, which was calculated from the conventional computed torque controller ($K_p = diag\ (300, 300, 300)$; $K_v = diag\ (35, 35, 35)$), uses triangular membership functions (for inputs and outputs) given by Figure 4:

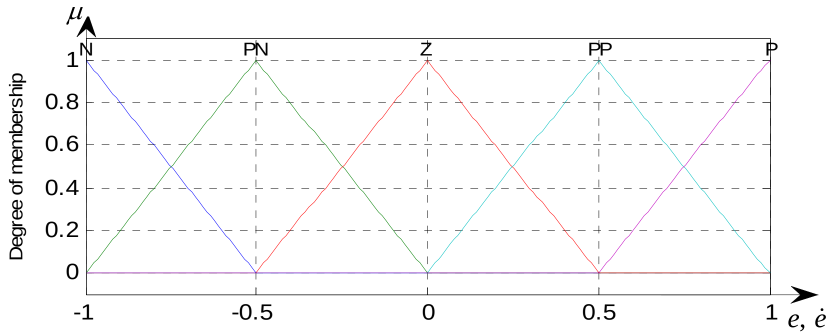
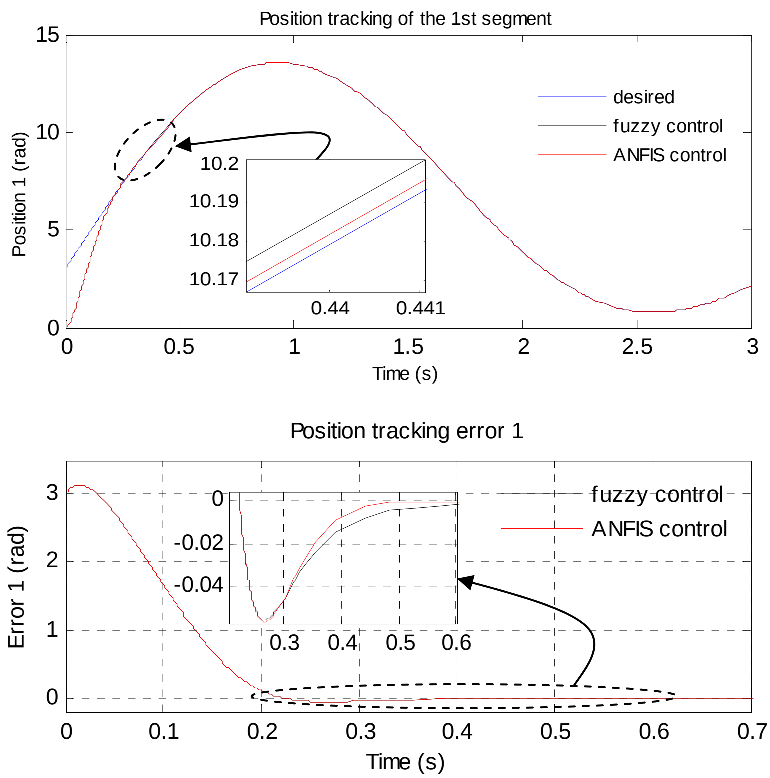
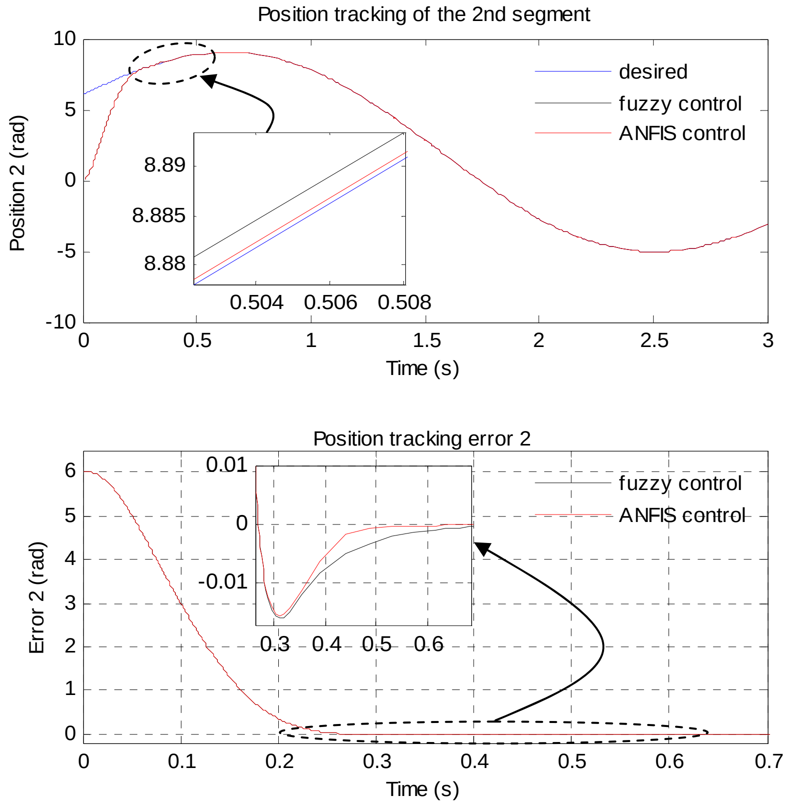


Figure 4. Membership function of the inputs and the outputs of the fuzzy controller

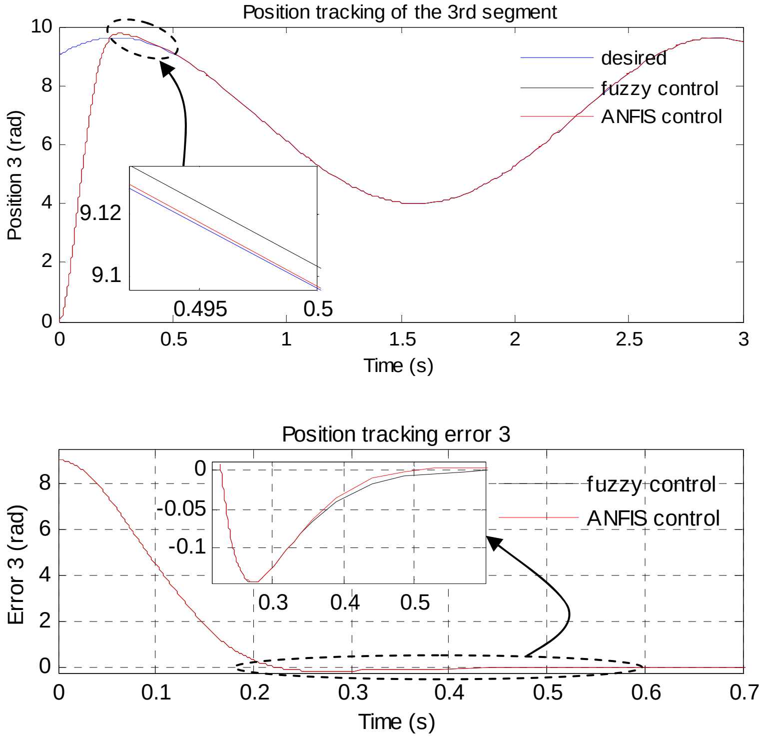
Figure 5, shows the behaviour of the robot in pursuit of the desired trajectory in both cases of the computed torque control, fuzzy logic and by ANFIS.



(*a*) First segment



(*b*) Second segment



(*c*) Third segment

Figure 5 (*a*, *b*, *c*). Trajectory pursuits of position and position errors with the fuzzy logic that by the ANFIS

We see clearly that the control performances by ANFIS are better than those in the fuzzy logic; this is interpreted by the faster convergence of position tracking error to zero (precision and stability), in the case of ANFIS controller. The robot reaches the desired trajectory in a time less than that of fuzzy control.

We found similar results for the case of the pursuit in velocity and acceleration.

5. CONCLUSION

In this article, we have presented a simple technique of control by ANFIS that contributes to improved performance of the linearizing control applied to robot manipulators.

The simulation results show that the ANFIS controller is better to fuzzy controller in robustness (adjustment of the rate of variations of the *PD* gains.) and in tracking precision and stability. The simulation study clearly indicates the finer performance of adaptive neuro-fuzzy control, because it is inherently adaptive in nature. It appears from the response properties that it has a high performance in presence of the plant parameters uncertain and unknown disturbances. It is used to control system with unknown model.

REFERENCES

[1] SPONG M. W., and M. Vidyasagar, "Robot Dynamics and Control," *John Wiley and Sons*, *Inc,* 1989.

[2] EGELAND O., "On the robustness of the computed torque technique in manipulator Control," *Proc.IEEE. Intern. Conf. Robotics and Automation,* 1986, p. 1203-1208.

[3] SUFIAN Ashraf Mazhari, Surendra Kumar Member IEEE, "Heuristic Search Algorithms for Tuning PUMA 560 Fuzzy PID Controller," *International Journal of Computer Science*, Jun. 2008, pp. 277-286.

[4] HALA Bezine, Nabil Derbel and Adel M. Alimi, "Fuzzy control of robot manipulators: some issues on design and rule base size reduction, " *Engineering Applications of Artificial Intelligence*, Sept 2002, vol. 15, Issue 5, pp. 401-416.

[5] J.S.R. Jang, " ANFIS: Adaptive-network-based fuzzy inference system, " *IEEE Trans Syst. Man. Cybernet*, 1993, 23(3), pp. 665-85.

[6] J.S.R. Jang, C.T. Sun, E. Mizutani, "Neuro-fuzzy and soft computing: A computational approach to learning and machine intelligence," 1997, *Upper Saddle River, Prentice-Hall*.

[7] V.A. Constantin, "Fuzzy logic and neuro-fuzzy applications explained," *Englewood Cliffs, 1995, Prentice-Hall.*

[8] C.T. Lin, C.S.G. Lee, "Neural fuzzy systems: A neuro-fuzzy synergism to intelligent systems," *Upper Saddle River, 1996, Prentice-Hall*.

[9] J. Kim, N. Kasabov: "HyFIS, Adaptive neuro-fuzzy inference systems and their application to nonlinear dynamical systems," *Neural Networks*, 1999, 12 (9), pp. 1301–19.

[10] G. MKHOURY, M.Saad, H.Y.Kannan, C.Asmar, "Fuzzy PID control of a Five DOF Robot Arm," *Journal of intelligent and robotic systems*, July 2004, vol. 40, pp. 299-320, ISSN: 0921-0296.

KADDOUR E. L., "Simulation de la commande dynamique d’un bras manipulteur à 6 ddl appliqué au robot puma 600," 1995, *USTO*.

BIBLIOGRAPHY OF AUTHORS

Ouamri Bachir was born in 1972 in Bejaïa, Algeria. He received his BS degree from the Electrical Engineering Institute of the University of Bejaïa in 1998, and the MS degree from the University of Oran in 2004. He is currently Assistant Professor of Electrical and Computer Engineering at the University of Bechar (Algeria). His current research interest includes intelligent process control, teleoperation, telerobotic and automation

Ahmed-Foitih Zoubir He received the Eng. Degree in Electronics in 1980, the Magister Degree in Automatic in 1988 and the Doctorat d’état in 2004 from the University of Sciences and Technology of Oran USTO (ORAN, Algeria). Since 1982 he is a lecturer and researcher member of the Electronics Department, U.S.T.O. His current research interest includes Robotic, Computer automation, control of industrial processes and supervision, Identification of process, Soft computing