INTELLIGENT INTERNAL MODEL CONTROL OF ROBOTS FOR UPPER-LIMB REHABILITATION

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Abstract: This paper presents a neuro-fuzzy internal model Cartesian controller for robot manipulators. An inductive learning technique is applied to generate the required inverse dynamics and inverse kinematics modelling rules from input/output measurements. A fully differentiable fuzzy neural network is used to construct the adaptive sections of the controller for on-line parameters adaptation. A fuzzy-PID-like incremental controller is employed as feedback servo-controller. The internal model Cartesian controller is implemented using inverse kinematics and forward kinematics models of the robot. The proposed control system was tested using a dynamics model of a six-axis industrial robot to perform upper-limb rehabilitation. The obtained results demonstrate the validity of the proposed control scheme.

Keywords: Dynamic systems, Fuzzy systems, Fuzzy-PID controllers, Internal model control, Neuro-fuzzy systems, Robot manipulators.

1. INTRODUCTION

It is usual in robot control systems to specify the desired trajectory in Cartesian coordinates as the task description is normally expressed in terms of a sequence of end-effector movements. Normally, this information is transformed into a series of angular positions in the joint space using a process called '*command generation*' (Vaccaro and Hill, 1988), so that the end-effector control is accomplished indirectly by controlling the joint angles. The transformation from joint coordinates to Cartesian coordinates is a vector-valued non-linear function which can be obtained in a straightforward way from the manipulator forward kinematics. However, the reverse transformation, the inverse kinematics, may not be unique and is known not to exist in closed form for certain manipulators. Fuzzy systems and neural networks have been used to approximate the inverse kinematics for robot manipulators (Sang-Bae, 1997; Martinez *et al.*, 1996; Kim *et al.*, 1993). This paper presents an adaptive neuro-fuzzy internal model Cartesian controller for robot manipulators (Li *et al.*, 1996). For this purpose, an inductive fuzzy learning technique introduced by Bigot (2003), was modified and used to generate the required inverse dynamics and inverse kinematics modelling rules. A fully differentiable fuzzy neural network was developed to construct the adaptive sections of the controller for on-line parameters adaptation. A fuzzy-PID-like incremental controller introduced by Shankir (2001) was modified and used as feedback servo-controller. The proposed control system was tested using a virtual dynamics model of the Puma 560 robot arm to perform upper-limb rehabilitation.

The remainder of the paper is organized as follows. Section (2) presents the overall structure of the proposed controller. Section (3) explains the proposed neuro-fuzzy network. Section (4) describes the fuzzy-PID-like servo-controller. Section (5) presents a robustness analysis for the proposed controller. Section (6) gives the results of controlling a Puma 560 to perform upper-limb rehabilitation using the proposed controller. Section (7) concludes the paper.

2. PROPOSED NEURO-FUZZY CONTROLLER

The structure of the proposed neuro-fuzzy control system is presented in Figures (1) and (2).

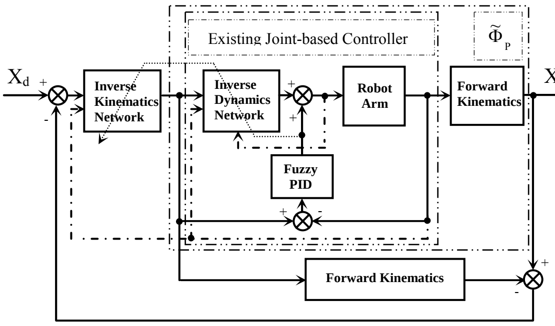

Fig.1. Proposed controller structure.

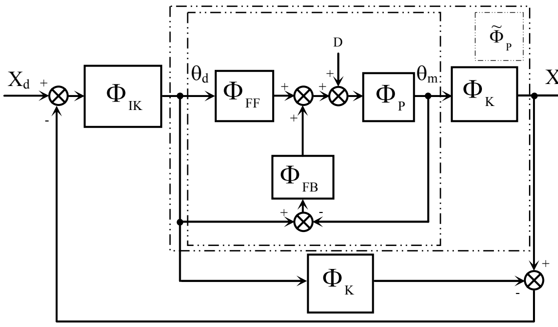

Fig.2. Simplified representation.

In the proposed control scheme, an approximate inverse kinematics model is employed as a Cartesian controller. A pre-compensation structure, which comprises a neuro-fuzzy inverse dynamics network and a feedback servo-controller, is used so that the internal model control (IMC) structure can be implemented using the inverse kinematics neuro-fuzzy network and the forward kinematics model of the robot arm to achieve adaptive Cartesian control. An adaptive '*command generator*' working for an existing joint-based inverse robot controller is obtained by introducing the inverse kinematics network outside the control loop to achieve compensation for robot Cartesian uncertainties through modifying the input Cartesian trajectory. The internal model represents the model of the robot in addition to the inverse joint-based controller cascaded by the forward kinematics model. From the simplified representation shown in figure (2), the input-output relationship (from X_d to X_m) can be directly derived as:

$$\Phi^R = [I + (\Phi_{IK}^{-1} - \Phi_K)\tilde{\Phi}_p^{-1}]^{-1} \tag{1}$$

where $\tilde{\Phi}_p$, the part surrounded by the dashed line, is the existing joint-based controller regarded as the pre-compensation structure of the robot dynamics, Φ_K is the robot forward kinematics model, and Φ_{IK} is the robot inverse kinematics model.

The input-output relationship (from θ_d to X_m) of the existing joint-based controller can be written as:

$$\begin{aligned}\tilde{\Phi}_p &= \frac{\Phi_K \Phi_P \left(\Phi_{FF} + \Phi_{FB}\right)}{\left(I + \Phi_P \Phi_{FB}\right)} \\ &= \Phi_K + \frac{\Phi_K \left(\Phi_P - \Phi_{FF}^{-1}\right)}{\Phi_{FF}^{-1}\left[I + \Phi_P \Phi_{FB}\right]}\end{aligned} \tag{2}$$

where Φ_P represents the robot arm dynamics, Φ_{FF} is the neuro-fuzzy inverse dynamics network regarded as the pre-lineariser, and Φ_{FB} is the fuzzy-PID-like servo-controller regarded as the stabilization element. Consequently equation (1) can be rewritten as:

$$\Phi^R = \left[I + \frac{\left(\Phi_{IK}^{-1} - \Phi_K\right)\left(I + \Phi_p \Phi_{FB}\right)}{\Phi_K \Phi_p \left[\Phi_{FF} + \Phi_{FB}\right]} \right]^{-1} \tag{3}$$

The overall Cartesian IMC can be considered a framework combining the neuro-fuzzy joint-based control structure, i.e. the pre-compensation structure, as the inner loop controller, with the general IMC structure as the outer loop controller. On the other hand, the IMC configuration can be regarded as an enhanced scheme for the neuro-fuzzy joint-based controller. This is because the outer loop structure in the IMC configuration, formed by Φ_{IK} and Φ_K, acts as an additional compensator for the original neuro-fuzzy joint-based controller.

The first step is to generate inverse dynamics and inverse kinematics modelling rules from input/output measurements using a fuzzy inductive learning algorithm introduced by Bigot (2003). This algorithm is designed to extract fuzzy IF-THEN rules from a collection of examples (training set). Initially, a manual step is performed to divide the output variable domain into target classes (fuzzy output membership functions, C_E). Here, each output variable is divided into equal, 50% overlapping Gaussian membership functions.

The algorithm incrementally employs a specific rule forming process until all examples are covered. The main feature of this process is that the conditions (membership functions) for inputs are created automatically during the rule forming process. At the end of the rule formation process, each condition takes the form ($V_1^i < A^i < V_2^i$), where V_1^i and V_2^i are continuous values included in the i^{th} attribute range (V_{min}^i, V_{max}^i). After the rule forming process, each continuous condition is transformed into a fuzzy condition in order to obtain the final fuzzy rule.

3. PROPOSED NEURO-FUZZY NETWORK

To model the inverse kinematics and inverse dynamics of the robot arm, a fuzzy rule-base is generated first using the aforementioned inductive learning method. Equations (4) & (5) express an approximation for both functions.

$$T_i^{k+1} \cong f\,(T_1^{k},\ldots, T_n^{k}, \theta_1^{k+1},\ldots, \theta_n^{k+1}, \theta_1^{k},\ldots, \theta_n^{k}, v_1^{k+1}, \ldots, v_n^{k+1}, v_1^{k},\ldots, v_n^{k}) \quad (4)$$

$$\theta_i^{k+1} \cong f(\, x^{k+1}, y^{k+1}, z^{k+1}, \theta_1^{k}, \theta_2^{k}, \ldots\ldots., \theta_n^{k}) \quad (5)$$

where k is the sampling interval, $i = (1,2,..., n)$, n is the number of joints, T is the joint torque, v is the joint velocity, θ is the joint angle, and (x, y, z) are the end-effector Cartesian position. The proposed network is a representation of the Mamdani-model-based feedforward fuzzy neural network. The network employs time-delayed feedback from the output layer to the input. The selected Gaussian and sigmoidal membership functions are differentiable and their parameters can be tuned on-line. To achieve effective application of the back-propagation learning method, the network employs differentiable alternatives for the *logic-min* and *logic-max* functions in its decision-making mechanism (Estevez and Nakano, 1995; Shankir, 2001).Figure (3) presents the structure of the proposed network consisting of six-layers. The first four layers have the same structure as the first four layers in (Lin and Lee, 1991), while the defuzzification function is represented using the last two layers. The *softmin and softmax* functions are used as layer (3) and layer (4) activation functions respectively.

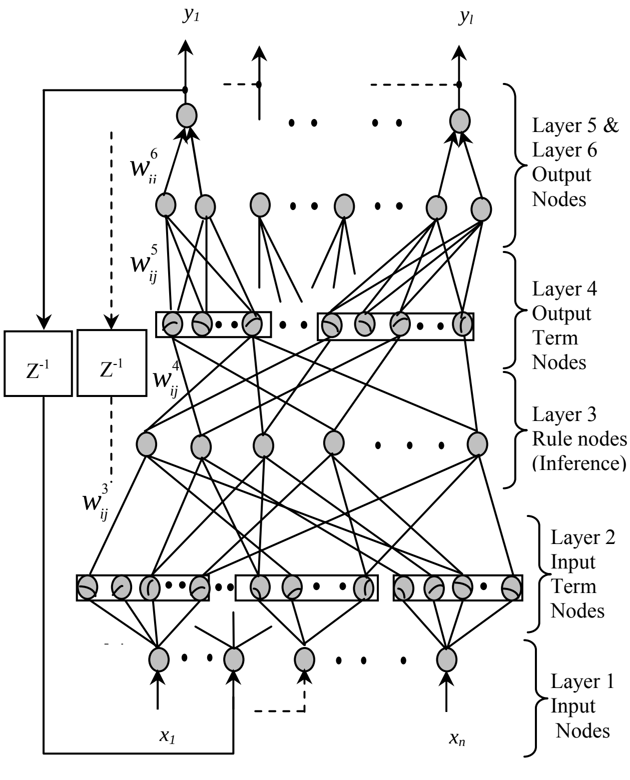

Fig.3. Proposed neuro-fuzzy network.

4. FUZZY-PID-LIKE SERVO-CONTROLLER

This controller employs two inputs, present and previous errors, and three outputs, P, I, and D. Each output element can approximate the corresponding (functional) control action with independent non-linear gain. The input and output universe of discourses are partitioned using five triangular fuzzy membership functions with 50% overlap.

The proportional, derivative and incremental part of the integral control actions of the fuzzy-PID-like incremental controller are functions of the two present and past normalized error variables. The partitions of the output universe of discourses are with different scaling factors to allow different tuning for each control element.

The fuzzy rules of the Fuzzy Proportional Control Element (FPCE) are generated heuristically based on the intuitive concept that the proportional control action at any time step is directly proportional to the error e_1 at the same time step. The fuzzy rules of the Fuzzy Derivative Control Element FDCE are generated based on the intuitive concept that the derivative control action at any time step is directly proportional to the error difference between two successive time steps. The fuzzy rules of the Fuzzy Incremental Integral Control Element (FICE) are generated based on the intuitive concept that the incremental part of the integral control action at a time step is directly proportional to the sum of the error variables at two successive time steps. The rule base of the three incremental FCEs (P, D, and I) is given in (Pham and Fahmy, 2005).

Feedback-Error Learning Scheme

Kawato *et al.* (Kawato *et al.*, 1988) proposed a novel architecture for adaptive control called the Feedback Error Learning (FEL) control technique. The neuro-fuzzy forward path controller parameters are tuned on-line using the feedback controller response as the error signal. This error signal is propagated through the inverse dynamics neuro-fuzzy network to the inverse kinematics neuro-fuzzy network to realise adaptive Cartesian control through on-line parameters optimization. The network adjustable parameters were selected to be centres of the output membership functions of the output term nodes in layer four as well as the link weights in layers two and six. The chain rule is then applied to calculate the network output partial derivatives with respect to the variable weights in each layer of the two networks.

It can be seen that by proper tuning of the parameters of the inverse kinematics neuro-fuzzy network, $\Phi_{IK}^{-1} \cong \Phi_K$, equation (1) can be reduced to $\Phi^R \cong I$, resulting in almost perfect Cartesian trajectory tracking.

5. ROBUSTNESS ANALYSIS

In this section, the proposed controller structure will be analyzed in terms of disturbance rejection and sensitivity to model uncertainties. The analysis will be compared with the original joint-based controller response to disturbance and model uncertainties to highlight the added benefits of the new structure.

5.1. Robustness Analysis

In robotic manipulators control, external disturbances are due to load torques acting at the joints as shown in figure (2). The disturbance transfer function for the neuro-fuzzy joint-based controller (from θ_d to X_m) is:

$$\tilde{\Phi}^D = \frac{\Phi_K \Phi_P}{I+\Phi_P\left(\Phi_{FB}\right)} \tag{6}$$

For the proposed neuro-fuzzy internal model Cartesian controller, the disturbance transfer function (from X_d to X_m) can be directly derived as:

$$\Phi^D = \frac{\Phi_K \Phi_P}{I+\Phi_P\left(\Phi_{FB} + \dfrac{\left(\Phi_{FF}+\Phi_{FB}\right)}{\left(\dfrac{I}{\Phi_K \Phi_{IK}}\right) - I}\right)} \tag{7}$$

By comparing equations (6) and (7), it can be seen that the effect of external disturbances for the modified IMC has been changed relative to the joint-based controller by the term $\dfrac{\left(\Phi_{FF}+\Phi_{FB}\right)}{\left(\dfrac{I}{\Phi_K \Phi_{IK}}\right) - I}$ in the denominator. This term has the possibility of producing an infinite value driving the disturbance transfer function to zero, resulting in a less sensitive control system compared to the original joint-based controller.

5.2. Sensitivity Analysis

Generally, in order to analyze the performance of any control system, it is common practice to replace the plant by its modelled dynamics Φ_m and possible model uncertainties as follows:

$$\Phi_p = (I + \delta\Phi_p)\Phi_m + \Delta\Phi_p \tag{8}$$

where $\delta\Phi_p$ and $\Delta\Phi_p$ are the multiplicative and additive uncertainties of the plant. Both kinds of uncertainties, which are due to unmodelled dynamics, will be examined separately.

5.2.1. Sensitivity to Multiplicative Uncertainties

For the neuro-fuzzy joint-based controller alone, the closed loop multiplicative sensitivity function is:

$$\xi^{\tilde{\Phi}_p}_{\partial\Phi_p} = \frac{\partial\tilde{\Phi}_p / \tilde{\Phi}_p}{\partial(\delta\Phi_p) / \delta\Phi_p} = \frac{\partial\tilde{\Phi}_p}{\partial\Phi_p}\frac{\partial\Phi_p}{\partial(\delta\Phi_p)}\frac{\delta\Phi_p}{\tilde{\Phi}_p}$$

$$= \frac{I}{I+\Phi_P\left(\Phi_{FB}\right)}\frac{\Phi_m}{\Phi_P}\delta\Phi_p \tag{9}$$

For the neuro-fuzzy Cartesian IMC controller, the closed loop multiplicative sensitivity function is:

$$\xi^{\Phi^R}_{\partial\Phi_p} = \frac{\partial\Phi^R / \Phi^R}{\partial(\delta\Phi_p) / \delta\Phi_p} = \frac{\partial\Phi^R}{\partial\Phi_p}\frac{\partial\Phi_p}{\partial(\delta\Phi_p)}\frac{\delta\Phi_p}{\Phi^R}$$

$$= \frac{I}{I+\Phi_P\left(\Phi_{FB} + \dfrac{\left(\Phi_{FF}+\Phi_{FB}\right)}{\left(\dfrac{I}{\Phi_K \Phi_{IK}}\right) - I}\right)}\frac{\Phi_m}{\Phi_P}\delta\Phi_p \tag{10}$$

By comparing equations (9) and (10), again it can be seen that the multiplicative sensitivity for the modified IMC has been changed relative to the existing joint-based controller by the term $\dfrac{\left(\Phi_{FF}+\Phi_{FB}\right)}{\left(\dfrac{I}{\Phi_K \Phi_{IK}}\right) - I}$ in the denominator. This term could produce an infinite value resulting in a less sensitive control system compared to the original joint-based controller.

5.2.2. Sensitivity to Additive Uncertainties

For the neuro-fuzzy joint-based controller alone, the closed loop additive sensitivity function is:

$$\xi^{\tilde{\Phi}_p}_{\Delta\Phi_p} = \frac{\partial\tilde{\Phi}_p \big/ \tilde{\Phi}_p}{\partial(\Delta\Phi_p) \big/ \Delta\Phi_p} = \frac{\partial\tilde{\Phi}_p}{\partial\Phi_p}\,\frac{\partial\Phi_p}{\partial(\Delta\Phi_p)}\,\frac{\Delta\Phi_p}{\tilde{\Phi}_p}$$

$$= \frac{I}{I+\Phi_p\left(\Phi_{FB}\right)}\,\frac{\Delta\Phi_p}{\Phi_p} \qquad (11)$$

For the IMC controller, the closed loop additive sensitivity function is:

$$\xi^{\Phi^R}_{\Delta\Phi_p} = \frac{\partial\Phi^R \big/ \Phi^R}{\partial(\Delta\Phi_p) \big/ \Delta\Phi_p} = \frac{\partial\Phi^R}{\partial\Phi_p}\,\frac{\partial\Phi_p}{\partial(\Delta\Phi_p)}\,\frac{\Delta\Phi_p}{\Phi^R}$$

$$= \frac{I}{I+\Phi_p\left(\Phi_{FB} + \dfrac{\left(\Phi_{FF}+\Phi_{FB}\right)}{\left(\dfrac{I}{\Phi_K\Phi_{IK}}\right) - I}\right)}\,\frac{\Delta\Phi_p}{\Phi_p} \qquad (12)$$

By comparing equations (11) and (12), again it can be seen that the additive sensitivity for the modified IMC contains the term $\dfrac{\left(\Phi_{FF}+\Phi_{FB}\right)}{\left(\dfrac{I}{\Phi_K\Phi_{IK}}\right)-I}$ in the denominator. This term could produce an infinite value resulting in a control system less sensitive to additive uncertainties compared to the original joint-based controller.

From the above analysis, it is clear that the overall performance of the system in the modified IMC structure should be better than that of the joint-based controller.

6. RESULTS

In 1999, the European Commission (EC) started a multi-national project, REHAROB, to produce a robotic system to administer physiotherapy to people with upper-limb impairments. The project brought together researchers with medical and engineering backgrounds to develop a system utilizing solutions in robotics and health care. The main objective of the REHAROB system is to minimize the time spent by physiotherapists in performing repetitive exercises by replacing physiotherapists by a robotized rehabilitation system. A library of exercises has been created by medical experts to include most of the exercises commonly performed by physiotherapists on patients with upper-limb problems. These exercises are encoded in the form of duration of the exercise, movement range, and patient posture (Pham *et al.*, 2001).

The proposed control system was tested on the first three links of the Puma 560 robot (Armstrong and Corke, 1994) while performing one of these exercises using a simplified model for the upper-limb as shown in figure (4).

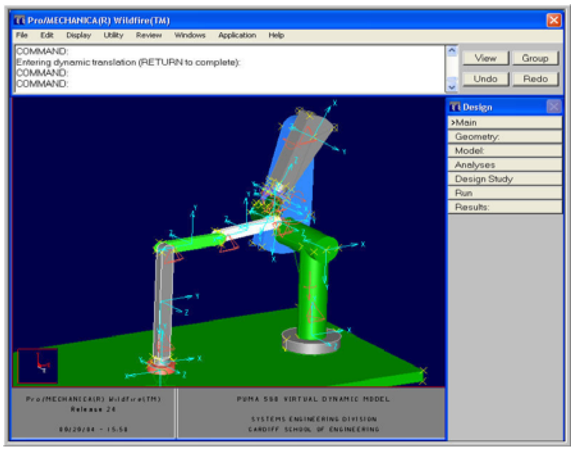

Fig.4. Simplified dynamic model for upper-limb rehabilitation using one robot.

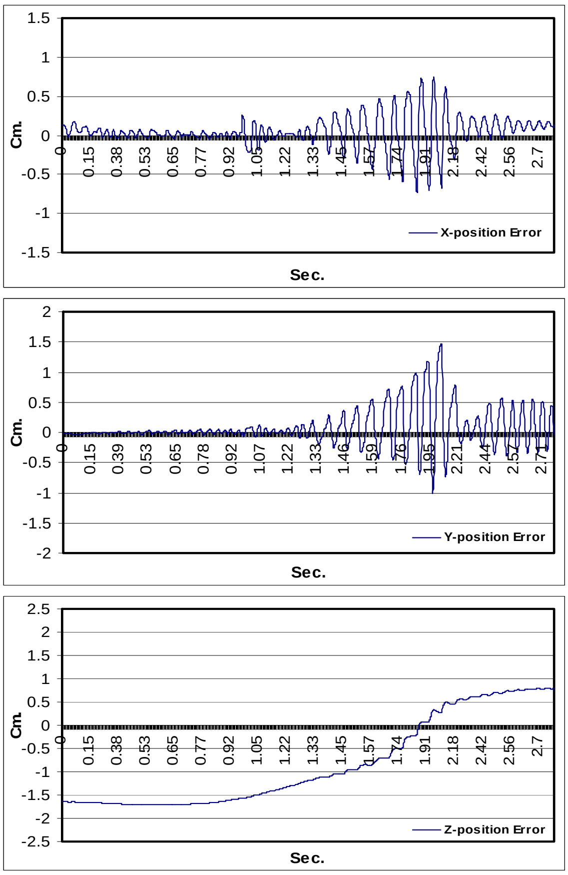

Fig.5. Proposed controller tracking errors.

Figure (5) presents the Cartesian position tracking errors for the neuro-fuzzy controller. The obtained results demonstrate the validity of the proposed control system in this upper-limb rehabilitation application.

7. CONCLUSION

A modified neuro-fuzzy internal model control strategy for Cartesian control of robotic manipulators has been proposed. The necessary structure modification is very simple and effective as it uses an approximate adaptive neuro-fuzzy inverse kinematics network in conjunction with a forward kinematics model to form an internal model scheme superimposed on an existing neuro-fuzzy joint-based controller. The control structure converts the command generation stage in robot control systems into an additional adaptive control loop which in turn increases the overall system robustness and disturbance rejection capabilities. A feedback error learning scheme was used to tune the weights of the neural networks on-line. It can be seen from the obtained results that the proposed control system was successfully applied for upper-limb rehabilitation.

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