Online Tracking Control System For Robot Manipulator Using Adaptive Fuzzy Wavelet Network

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Abstract

It is well known that Wavelet Networks (WN) are powerful tools for handling problems of large dimensions. The integration of Wavelet Network and Fuzzy Logic (FL) enable a tool condition monitoring system to have a high monitoring success rate and fast training feed over a wide range of cutting conditions in drilling applications. To overcome offline learning and to perform efficient tracking behavior, an Auto Tuning Adaptive Fuzzy Wavelet Network (ATAFWN) controller is proposed. It was shown that such structure don't need offline learning to govern the system in stable regions. It can be handle also a wide range of parameter changes in comparison with the conventional controller as well as such controller is simple to configure since it doesn't need a process model and can be easily adapted to the existing controller and plants.

Keywords: online controller, fuzzy logic, wavelet network, fuzzy wavelet network.

نظام سيطرة تتبع آني لحركة ذراع آلي باستخدام شبكة المويجه المضببه المتكيفة

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الخلاصة

مما لا شك فيه أن تقنية شبكة المويجه استطاعت التغلب على مشكلة الأبعاد الكبيرة للاشاره. وكان لدمج تقنية شبكة المويجه مع تقنية المنطق المضبب الأثر الواضح في تحسين مراقبة الأنظمة وسرعة في التدريب للانظمه المعقدة منقوصة المعلومات. للتغلب على مشكلة التدريب المسبق ولزيادة كفاءة سلوك النظام، تم اقتراح مسيطر توليف ذاتي لشبكة المويجة المضببة المتكيفة. وأظهرت النتائج أن هذا المسيطر لا يحتاج إلى تدريب مسبق لجعل النظام مستقرا. كما وأظهرت النتائج أن المسيطر المقترح استطاع الصمود بوجه التغيرات الطارئه على متغيرات النظام، بالاضافه إلى كل ما سبق فان المسيطر المقترح يعتبر سهل التنصيب خاصة وانه لا يحتاج لمعرفه مسبقة بالنظام المراد السيطرة عليه.

Received 26 Nov. 2006 **Accepted 9 May 2007**

1. Introduction

In recent years, controller design for systems having complex nonlinear dynamics becomes an important and challenging topic. Many remarkable results in this area have been obtained owing to the advances in geometric nonlinear control theory, and in particular, feedback linearization techniques. Both state feedback and output feedback linearization methods were studied in the literature. Under certain assumptions, these output feedback controllers can guarantee the global stability of the closed-loop systems based on state observers. Applications of these approaches are quite limited because they rely on the exact knowledge of the plant nonlinearities. In order to relax some of the exact model matching restrictions, several adaptive schemes have recently been introduced to solve the problem of parametric uncertainties. At the present stage they are only applicable to a kind of affine systems which can be linearly parameterized.

Recently, wavelets have become a very active subject in both mathematic and engineering research areas. However wavelets are usually limited to small dimension since constructing and storing wavelet basis of large dimension is very difficult. Wavelet networks (WN)s have been developed to overcome this limitation[1].Fuzzy Wavelet Network (FWN) is based on the integration of fuzzy logic, wavelet transform and artificial neural networks theories. This new schemes give an ability of self learning and self organizing, it can merge these techniques within the same system. It is shown here that it is possible to train WN learning and interpret the knowledge that is acquired from linguistic form, as well as it is very easy to define the initial values of parameters in WN form linguistic rules.

2. Wavelet Neural Network

In this section, some basic concepts in Wavelet Network are briefly recalled. Starting with the discussing of the basic wavelet analysis theory. Suppose that $V_i, \quad \forall i \in Z$ is the closed space [2]:

(1) the sequence of the space V_i is nested, *i.e.*, $\ldots \subset V_{-1} \subset V_0 \subset V_1 \ldots,$

(2) $\cap_{i \in Z} V_i = \{0\}$

(3) $V_{i+1} = \quad V_i \oplus W_i, \quad \forall i \in Z,$

(4) $f(t) \in V_i \Leftrightarrow f(2t) \in V_{i+1}, \quad \forall i \in Z,$

where Z is the set of all integers, $\cap$ is the intersection operator and $\oplus$ is the direct sum. Whole space S can be written as follows: $S = V \oplus W_i \oplus W_{i+1} \oplus \ldots.. \oplus W_0 \oplus W_1 \oplus \ldots., \quad for \quad i \in Z$

Now consider a function *f(t)* in *S*. it can be rewritten as [3]:

$$\hat{f}(t) = x(t) \sum_{k=1}^{K} w_k \psi_{a_k, b_k}(t) \qquad (1)$$

where w_k are the weighted coefficients and $\psi_{a_k,b_k}(t)$ is a set of daughter wavelets that generated by dilation a and translation b from a mother wavelet $\psi(t)$:

$$\psi_{a,b}(t) = \psi\left(\frac{t-b}{a}\right)$$
(2)

With the dilation factor $a > 0$. The wavelon parameters w_k, a_k and b_k can be optimized in the LMS algorithm by minimizing a cost function or the energy function E over all time t, thus by denoting $e(t)$ be a time-varying error function at time t [4]:

$$e(t) = f(t) - \hat{f}(t)$$
(3)

where $f(t)$ is the desired (target) signal and $\hat{f}(t)$ is the estimated signal. Hence the energy function will be defined by

$$E = \frac{1}{2}\sum_{t=1}^{T} e^2(t)$$
(4)

where T is the length of the desired signal.

In the minimization of E the method of steepest descent is used here. This requires the computation of gradients $\frac{\partial E}{\partial w_k}$, $\frac{\partial E}{\partial a_k}$ and $\frac{\partial E}{\partial b_k}$ for the purpose of updating the incremental changes to each particular parameter w_k, a_k and b_k, respectively. Several mother wavelets are considered and used here and these are given in [3].

3. Structure of Adaptive Fuzzy Wavelet Network

Motivated by the reason stated in section I, A new type of fuzzy wavelet-based model will be proposed, called adaptive fuzzy wavelet networks (AFWN) is presented; the main block diagram of this proposed Fuzzy Wavelet Network FWN is given in Figure 1. This structure introduces a multi input multi output MIMO function approximator model. It consists of four layers namely: the input layer, Fuzzification layer, rule layer and defuzzification layer.

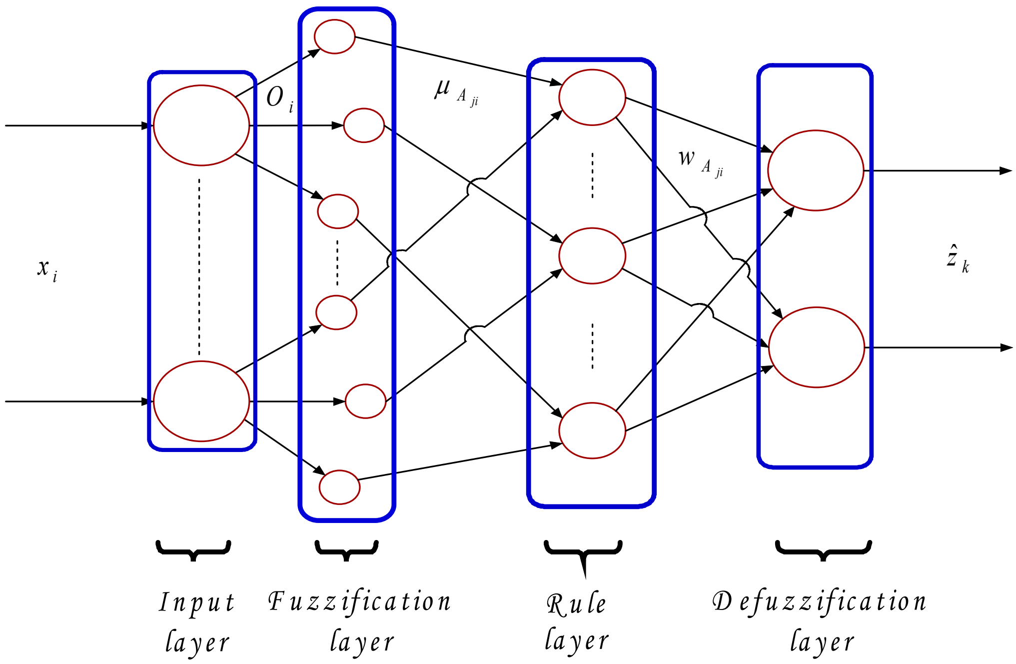


Figure 1: Structure of Fuzzy Wavelet Networks

The computation of the AFWN is illustrated in the following steps:

Step One: The Fuzzification Setup: In this step it is necessary to build the Fuzzification membership through the following procedure.

a) The input to the structure, input layer, is x_i and its outputs o_i will be given to the Fuzzification layer

$$o_i = x_i, \qquad i = 1,2,....,N \tag{5}$$

where N is the number of inputs.

b) For each fuzzy term A_{ji} in jth rule, associated with ith input o_i, the membership $\mu_{A_{ji}}$ is

$$\mu_{A_{ji}}(t) = x_i(t).\psi_{a_{ji},b_{ji}}(t) \tag{6}$$

The previous structure of WN is extended to be used here as a membership function by translating and dilating the mother wavelet basis function to build up Fuzzification layer. It is shown that a set of 10 to 40 Wavelet basis functions memberships is required for its success.

Step Two: Selection of Implicator Rule: This requires setting of the implicators rules that are necessary for convergence of the network. The number of implicators used here is equal to the number of memberships, which use minimum operation implicator.

Step Three: The Defuzzification Setup: The fourth layer in AFWN is the output layer, which realizes using: $\hat{z}_k = \sum_{j=1}^{J} w_{jk} y_j$ to produce crisp output value.

Step Four: The Learning Algorithm of the Proposed AFWN: The gradient descent algorithms for tuning the parameters, dilations a_{ji} , translations b_{ji} and weights w_{jk} of the AFWN is used to modify (update) only the gene that activates (or is firing) specific rule.

First the following *cost function (E)* for this case was used:

$$E = \frac{1}{2K} \sum_{t=1}^{T} \sum_{k=1}^{K} (\hat{z}_k(t) - z_k(t))^2$$

(7)

where $z_k(t)$ is the *kth* desired output, $\hat{z}_k(t)$ is the *kth* approximated output of FWN, K is the number of output signals and T is the length of the output signal. The training algorithm, which is extended from WN training algorithm is used to update the parameters of FWN, dilations a_{ji} , translations b_{ji} and weights w_{jk}, such as to minimize the cost function *(E)*. Thus the FWN weights can be update using the following equations:

$$w_{jk}(k+1) = w_{jk}(k) - \eta_1 \frac{\partial E}{\partial w_{jk}},$$

$$a_{ji}(k+1) = a_{ji}(k) - \eta_2 \frac{\partial E}{\partial a_{ji}},$$

$$b_{ji}(k+1) = b_{ji}(k) - \eta_3 \frac{\partial E}{\partial b_{ji}},$$

(8)

where:

$$\frac{\partial E}{\partial w_{jk}} = -\sum_{t=1}^{T} e(t)\psi(\tau)o_i(t),$$
$$\frac{\partial E}{\partial b_{ji}} = -\sum_{t=1}^{T} e(t)o_i w_{jk} \frac{\partial \psi(\tau)}{\partial b_{ji}},$$
$$\frac{\partial E}{\partial a_{ji}} = -\sum_{t=1}^{T} e(t)o_i w_{jk} \tau \frac{\partial \psi(\tau)}{\partial b_{ji}} = \tau \frac{\partial E}{\partial b_{ji}}, \tag{9}$$

where: $\tau = \frac{t - b_{ji}}{a_{ji}}$, i is the input indicator, j is the rule indicator, k is the output indicator, μ_A is the membership function which is here considered as the mother wavelet basis function and o_i is the output of the input layer.

4. Problem Formulation

In this section the control laws derived by linearization techniques as state in [5] will be modified by the proposed AFWN obtained in previous section to provide an online tracking control on a two flexible joints robot manipulator system. The simulation of two flexible joints robot manipulator considers the following parameters [6].

I : Moment of inertia of the load $= 1\ kg.m.s^2$

M : Rotor mass $= 1\ kg$

g : Gravity $= 9.8\ m/s^2$

ℓ : Length of the arm $= 1\ m$

k : Stiffness coefficient of the motor $= 100\ kg.m/A$

J : Moment of inertia of the motor $= 1\ kg.m.s^2$

The nonlinear state space of the robot manipulator is given by the following model

$$\dot{x} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -\frac{Mgl}{I}\sin(x_1) - \frac{k}{I} & 0 & \frac{k}{I} & 0 \\ 0 & 0 & 0 & 1 \\ \frac{k}{J} & 0 & -\frac{k}{J} & 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} u$$

$$\dot{x} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -9.8\sin(x_1) - 100 & 0 & 100 & 0 \\ 0 & 0 & 0 & 1 \\ 100 & 0 & -100 & 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} u$$

(10)

Applying the linearization technique, the state transformation (feedback control law) and the control action (feed forward control law) are respectively given by:

$$\begin{aligned} y_1 &= x_1 \\ y_2 &= x_2 \\ y_3 &= -\frac{Mgl}{I}\sin(x_1) - \frac{k}{I}(x_1 - x_3) \\ y_4 &= -\frac{Mgl}{I}\cos(x_1)x_2 - \frac{k}{I}(x_2 - x_4) \end{aligned}$$

$$\begin{aligned} y_1 &= x_1 \\ y_2 &= x_2 \\ y_3 &= -9.8\sin(x_1) - 100(x_1 - x_3) \\ y_4 &= -9.8\cos(x_1)x_2 - 100(x_2 - x_4) \end{aligned}$$

(11)

$$u = \frac{IJ}{k}v - \frac{MglJ}{k}\sin(x_1)(x_2^2 + \frac{Mgl}{I}\cos(x_1) + \frac{k}{I}) \\ - J(x_1 - x_3)(\frac{k}{I} + \frac{k}{J} + \frac{Mgl}{I}\cos(x_1))$$

$$u = \frac{1}{100}\left(v - \left[9.8\sin(x_1)(x_2{}^2 + 9.8\cos(x_1) + 100) \right.\right. \\ \left.\left. + 100(x_1 - x_3)(100 + 100 + 9.8\cos(x_1))\right]\right)$$

(12)

The outer loop design is completed by design of an optimal state feedback regulator for the linearized model ($1/s^4$), [7]. The normalized gain matrix is:

$$K = [1 \quad 0.454 \quad 0.0861 \quad 0.0068].$$

Figure 2 shows both outer and inner loop design based on linearization technique and optimal control theory for the considered two flexible joints robot manipulator.

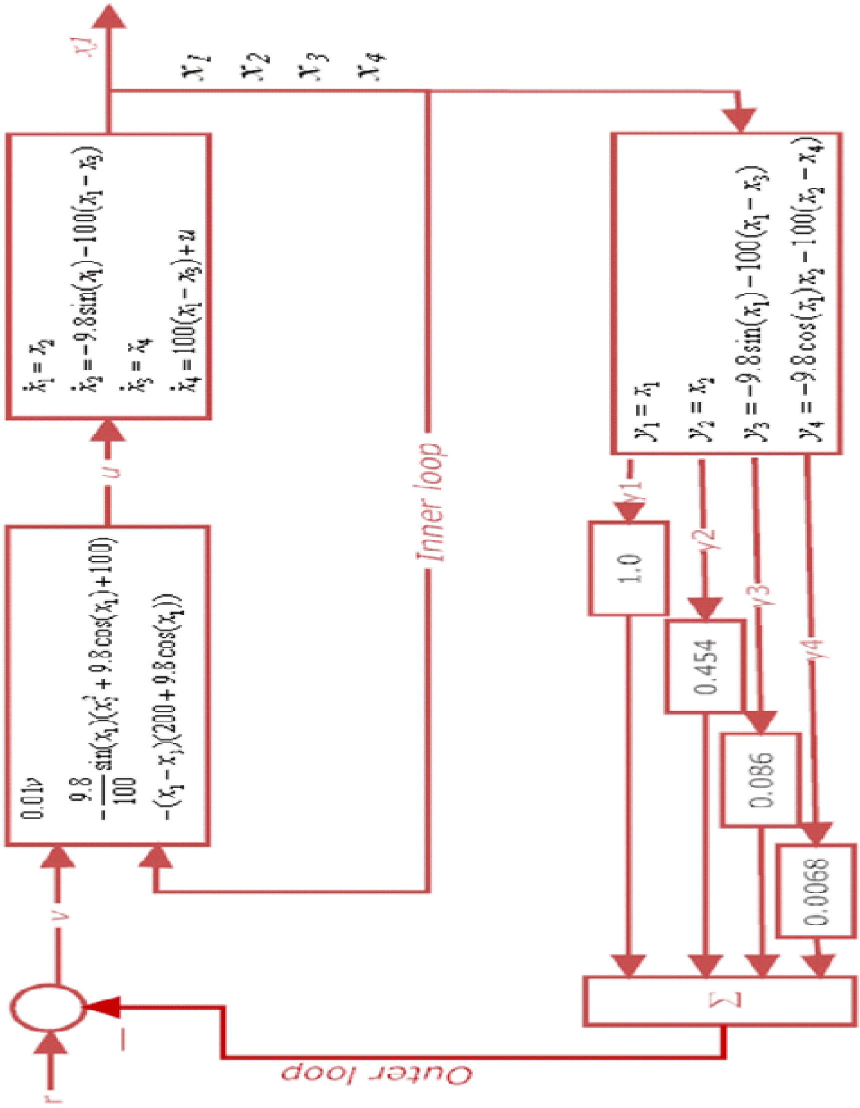


Figure 2 : Robot and Control system structure using feedback linearization technique

A Matlab program has been performed to obtain the nominal values of the system states, transformed states and the control input, and on the other side to link this program with the proposed software of implementing AFWN.

The object now is to replace the forward control law given in (12) by the proposed AFWN of 40-Rasp1 structure and evaluate the controlled system response for nominal conditions. Figure 3 shows the proposed online tracking control system, and Figure 4 shows the system step responses for both cases; with linearized control law and with proposed AFWN. As it is clearly seen no significant difference is there, which indicates successful replacement. However it is important to say that till now no dynamic charges have been considered to test the proposed AFWN and the successful replacement is nothing than a static fitting of data to certain nonlinear function. In the next section a dynamic situation will be considered.

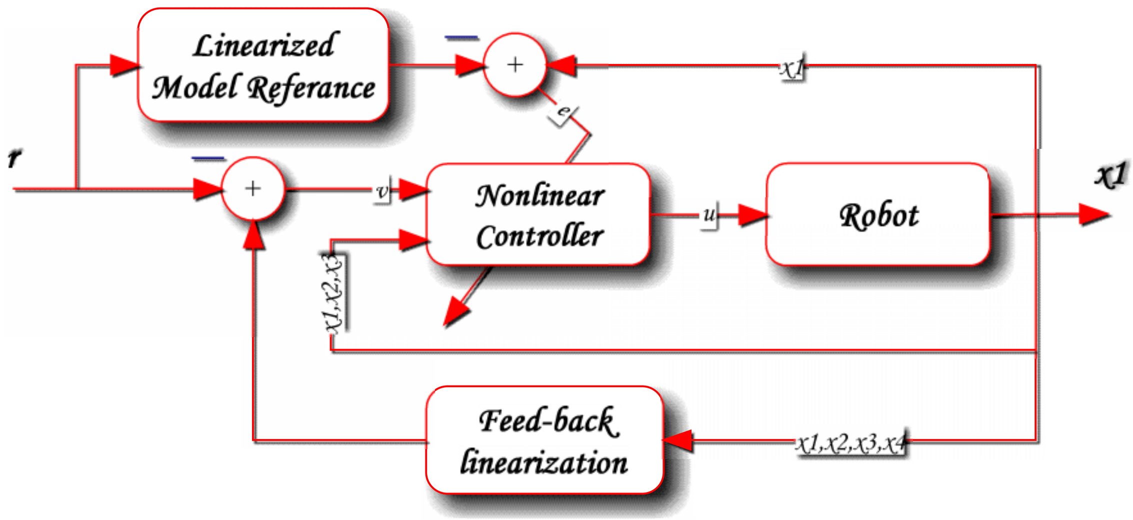


Figure3 : Adaptive Online Learning Forward Controller

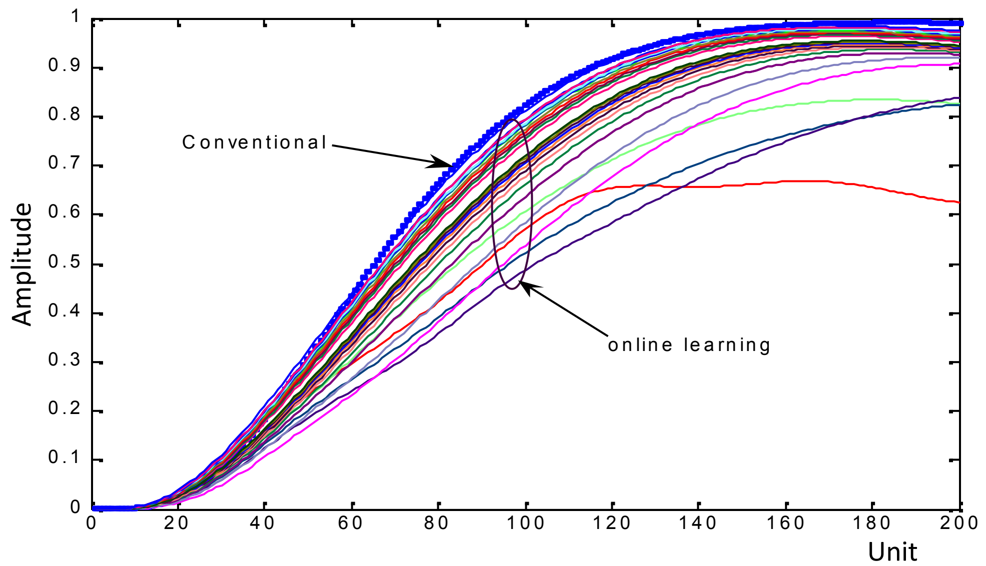


Figure 4 : System Step responses using conventional control law and AFWN as a Feed forward controller with several attempts

5. Robustness Performance of AFWN Controller

Due to many physical environments the value of robot parameters may be deviated from their nominal values, and hence the robustness degree of any used controller must be under investigation. In [5]-[7] it is shown thoroughly how the performance of the robot manipulator controlled by feedback linearization technique is degraded from its nominal response as the parameters change. In what follows the proposed AFWN will be used as a feed forward controller where the nonparametric dynamic functions v, x_1, x_2 and x_3 represent the elements of the input vector to AFWN and u represents its output signal. Different hypothetical cases of changing the moment of inertia of the motor J and the moment of inertia of the load I are within specific ranges.

In this phase, the motor moment of inertia J is varied up and down of its nominal value by 50%. Fig.(5) shows the robot manipulation normalized responses for unit step input when J is increased up to $\pm$ 50% of its nominal value. The maximum increment of the overshoot is less than $\pm$ 1.15%, while the maximum steady-state error is 0.0075. Similarly Fig. (6) illustrates the responses for unit step input when I is varied up to

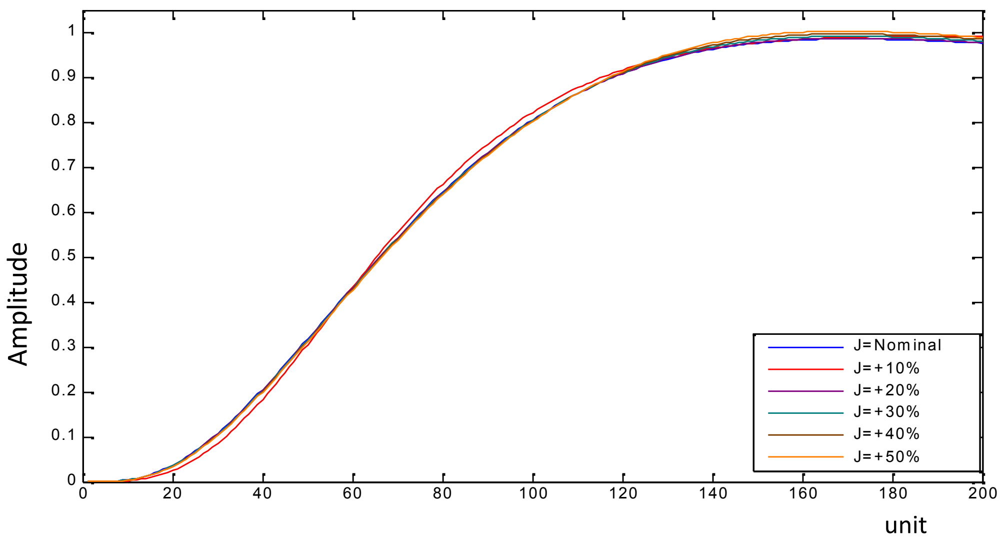
± 50% of its nominal, *a* maximum steady-state error of about 0.07 can be clearly defined. Therefore one can say that the performance of the proposed AFWN controller in such dynamic environments exhibits a robust behavior. However as the load moment of inertia *I* and motor of inertia *J* are varied such robustness clearly can be achieved, and the system response stacks on stable region and try to reach an optimal response as the controlled system still work.

Unlike the controllers suggested in [5]-[7], here the contributed controller, had numerous benefits which can be summarized as follow:

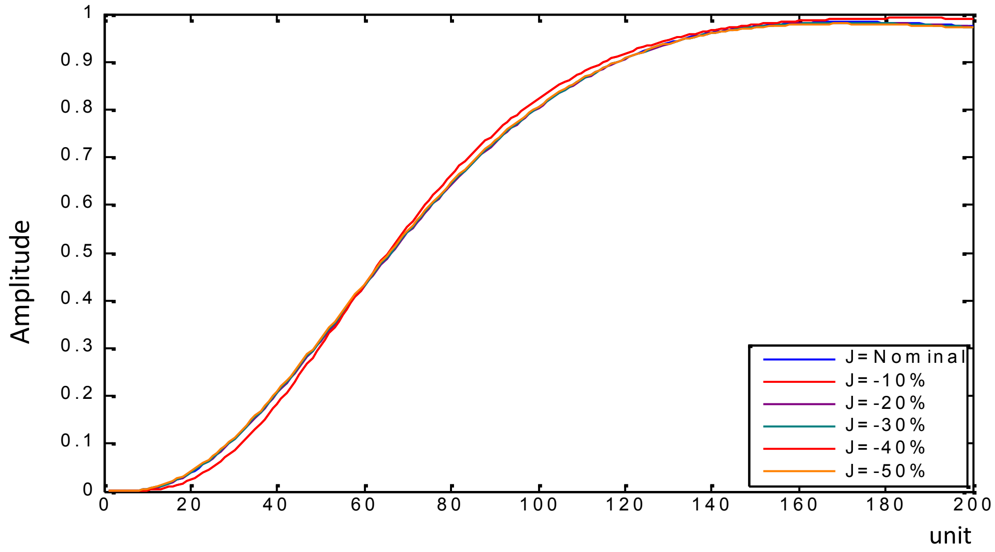
1- There is no need to offline learning.

2- More capable to overcome variation of system parameters.

3- System behavior is optimized as much as it is work.



(a)(Continue)

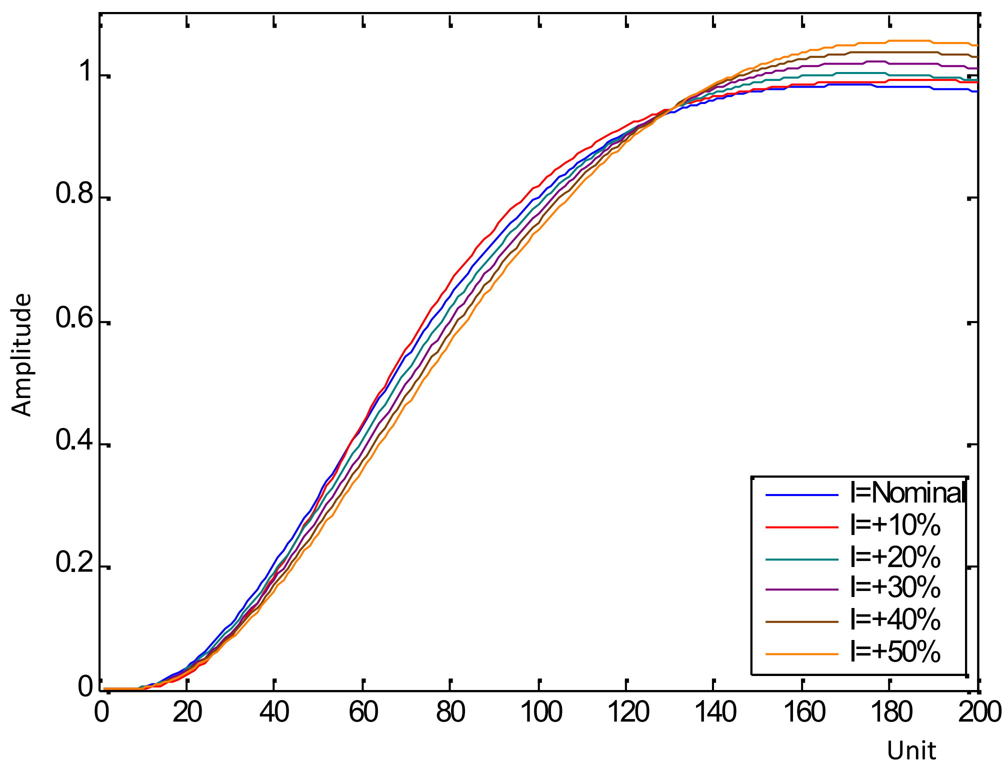


(b)

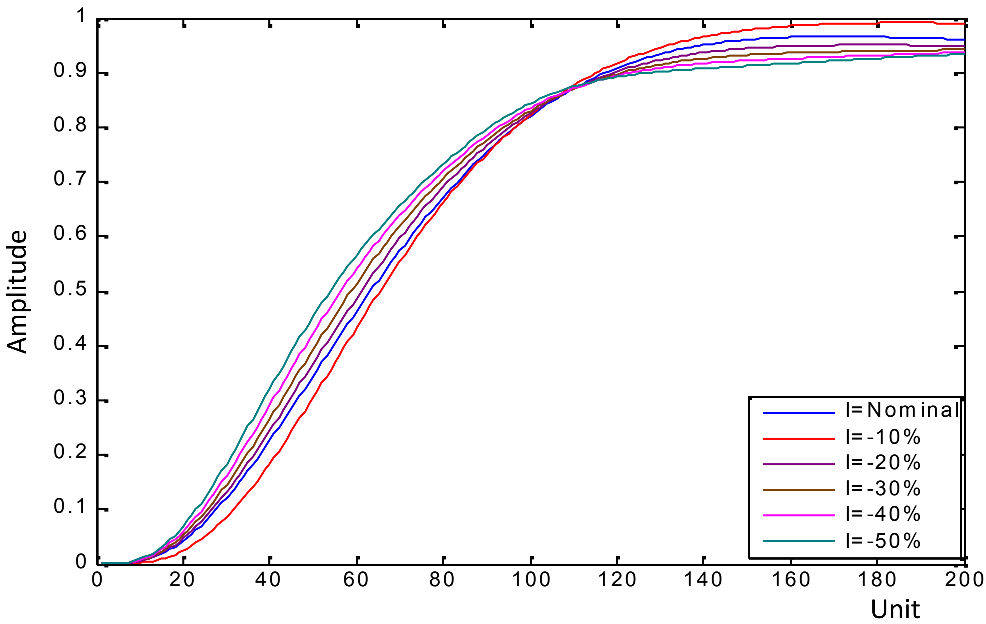
Figure 5 : Unit step response as J varies between ± 50%

(a) Unit step response as J increases up to 50%

(b) Unit step response as J decreases down to -50%



(a) (Continue)



(b)

Figure 6 : Unit step response as I varies between ± 50%

(a) Unit step response as I increases up to 50%

(b) Unit step response as I decreases down to -50%

Conclusion

A new type of network, called AFWN has been introduced for solve tracking control problem under the case of parameters variation of Robot manipulation. The proposed AFWN uses Wavelet Network to realize Fuzzification, fuzzy inference and defuzzification. It has many advantages, such as that it's structure, activation functions in neurons and weights, so it can be easily initialized according to fuzzy linguistic rules.

This proposed AFWN are used to control two flexible joint robot manipulators.

Promising results were caught with respect to conventional controller. It was mentioned that the amount of moment of inertia of the motor J can vary up to $\mp 50\%$ without sever degradation in system performance when AFWN are used, while the system goes to unstable region when J decrease to -5% of its nominal value when conventional controller are used. Similar conclusions also can be derived for the moment of inertia of the load I ,that only $\mp 1\%$ vary of its nominal value is sufficient to achieve system in unstable region if the conventional controller are used; while using AFWN force the system to stay on the stable region despite a wide range of varying in I, here above of $\mp 50\%$ of the nominal value give an acceptable performance.

In summary, the presented AFWN is not only reserved the multi resolution capability of WN, but also has the advantages of high approximation accuracy. It is believed that AFWN can be applied to the problems of function approximation, system identification, signal processing and control.

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