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Adaptive Neural Network Control for Inverted Pendulum Using Backstepping with Uncertainties

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Abstract

In this paper, an adaptive network backstepping control for a class of uncertain nonlinear systems is presented and applied to an inverted pendulum. The proposed technique will provide useful solutions when dealing with: unknown nonlinearities; unknown system parameters; external or internal disturbances and stabilization in a desired position. A specific type of artificial neural networks called Multilayer Perceptron is used and simulation results clearly demonstrate the power of this approach.

Keywords: *Adaptive backstepping, disturbances, uncertain nonlinear systems, Multilayer Perceptron (MLP)*

1. Introduction

An inverted pendulum is a physical device consisting of a cylindrical rod (usually aluminium) free to oscillate about a fixed pivot. The pivot is mounted on a cart, which in its turn can move along a horizontal direction. The cart is driven by a motor, which can exert on it a variable force. The rod tends to fall naturally down from the vertical position, which is an unstable equilibrium position [1].

Through simulations and experiments, the inverted pendulum is a practical example to validate a control technique (*e.g.*, PID; state space and fuzzy controllers, etc.).

In recent years, much progress has been made in the field of control of nonlinear systems. Backstepping technique is one of these new breakthroughs in this field. It was developed by Kanellakopoulos *et al.*, in the 90s and was inspired by the work of Morse and Feurer on one hand and Tsinias, Kokotović, Sussmann on the other. The main advantage of this method is to ensure system stability with adaptive control. It is also used to determine the control law and parameters updating laws ([2-4]).

The neural network techniques have been found to be particularly useful for the control of nonlinear systems with uncertain parameters. The theoretical background of this work and its history can be found in ([5-12]). In particular [10], Polycarpou developed a neural adaptive control for uncertain nonlinear systems in strict-feedback form using backstepping technique. This approach has expanded the condition of adaptation. The design procedure was applied using linearly parameterized neural networks such as *RBF* networks with fixed centers and widths. Polycarpou and Mears have also developed adaptive control laws using neural approximations with nonlinearities set [11]. More recently, Kwan and Lewis developed an adaptive control (multi-input-multi-output) to a more general class [13]. Their paper presented a general and uniform approach to the backstepping control nonlinear strict-feedback form using

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neural networks systems. Dan Wang and Jie Huang developed a neural backstepping control algorithm in a professional manner using the *MLP* networks to approximate the unknown nonlinear functions [14]. For Elleuch and Damakthe, the objective was to expand the space problem by introducing perturbations for a general model and generate a robust algorithm [15].

In this paper, an adaptive neural backstepping control is synthesized and applied to an inverted pendulum. The proposed technique is built from two basic control structures namely non adaptive and adaptive backstepping control, considered as a starting point and theoretical background.

2. Inverted Pendulum Model

The system under consideration is depicted on figure1. Its model can be expressed by using the following state variables $x, \dot{x}, \theta, \dot{\theta}$; where x is the position of the cart, θ is the angle of the rod, $\vec{F}$ is the force acting on the cart, m and M are respectively the masses of the rod and the cart.

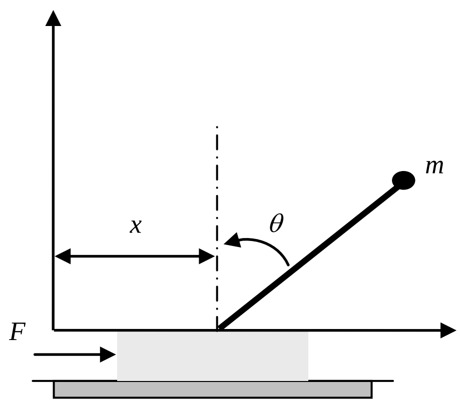


Figure 1. Inverted Pendulum Scheme

For sake of state representation simplicity and backstepping algorithm application, the angular acceleration of the rod is considered as the system input rather than the force F. The inverted pendulum model without disturbances can be found in ([8, 16], 17]).

In the presence of disturbances, the model under study takes into consideration the following state variables:

$$x_1 = x, \quad x_2 = \dot{x}, \quad x_3 = q, \quad x_4 = \dot{q}$$

$$\begin{cases} \dot{x}_1 = x_2 + \eta_1(x, \omega, t) \\ \dot{x}_2 = \varphi_2 - \dfrac{1}{\cos x_3} u + \eta_2(x, \omega, t) \\ \dot{x}_3 = x_4 + \eta_3(x, \omega, t) \\ \dot{x}_4 = \varphi_4 + \dfrac{1}{\ell} u + \eta_4(x, \omega, t) \end{cases} \tag{1}$$

where:

$$\varphi_2 = g\ tg\ x_3 + \frac{m\ l\ (sinx_3)\ x_4^2}{M + m.sin^2 x_3}\ ;\ \varphi_4 = -\frac{m\ x_4^2 sinx_3\ cosx_3}{m.sin^2 x_3 + M} \tag{2}$$

g is the gravitational acceleration and ℓ is the length of the rod;

η_i : are all disturbances (external and internal) ; ω : is the unknown parameter vector.

3. Non Adaptive Backstepping Control

In the following, the different steps are developed for deducing the control law. In this case, the system parameters are assumed known.

- **Step 1**

The aim is to control the desired angular position. Thus, we opted for the first variable error:

$$z_3 = x_3 - y_r \tag{3}$$

and to determine the system stability, the first Lyapunov function is defined by:

$$\vartheta_3 = \frac{1}{2} z_3^{\ 2} \tag{4}$$

Its derivative leads to:

$$\dot{\vartheta}_3 = z_3 \dot{z}_3 = z_3 (x_4 + \eta_3 - \dot{y}_r) \tag{5}$$

This will give the following stabilizing function:

$$\alpha = x_{4d} - \dot{y}_r = -c_3 z_3 - h_3 \tag{6}$$

where η_3 is bounded by a positive value h_3 , $|\eta_3| \le h_3$.

Then, equation (5) becomes:

$$\dot{\vartheta}_3 = -c_3 z_3^{\ 2} + z_3.z_4 + z_3 (\eta_3 - h_3) \tag{7}$$

- **Step 2**

The second variable error is chosen as follows:

$$z_4 = x_4 - \alpha - \dot{y}_r \tag{8}$$

and the second Lyapunov function can be represented by the following expression:

$$\vartheta_4 = \vartheta_3 + \frac{1}{2} z_4^{\ 2} \tag{9}$$

Using equations (1), (6),(7) and (9), the derivative of the previous function leads to:

$$\dot{\vartheta}_4 = -c_3 z_3^{\ 2} - c_4 z_4^{\ 2} + z_4 \left(z_3 + c_4 z_4 + \varphi_4 + \eta_4 + \frac{1}{\ell}.u + c_3 (x_4 + \eta_3) - c_3 \dot{y}_r - \ddot{y}_r \right) + z_3 (\eta_3 - h_3) \tag{10}$$

Finally, the non adaptive control law is obtained as follows:

$$u = -\ell [z_3 + c_4 z_4 + +\varphi_4 + h_4 + c_3(x_4 + h_3) - c_3 \dot{y}_r - \ddot{y}_r] \quad (11)$$

4. Adaptive backstepping control

For adaptive control case, the supposed unknown length ℓ will be estimated. Practically, the same steps will be followed, and the Lyapunov function takes the expression below:

$$\vartheta_5 = \vartheta_4 + \frac{1}{2\gamma}\tilde{\beta}^2 \quad (12)$$

with: $\beta = 1/\ell$ and $\beta = \hat{\beta} + \tilde{\beta}$

So, the control law deduced in this case will have the following form:

$$u = -\hat{\ell} [z_3 + c_4 z_4 + \varphi_4 + h_4 + c_3(x_4 + h_3) - c_3 \dot{y}_r - \ddot{y}_r] \quad (13)$$

and the adaptation dynamics is as follows:

$$\dot{\hat{\ell}} = \gamma z_4 u \quad (14)$$

where γ is the adaptation gain.

5. Adaptive neural network control using backstepping with uncertainties

In the subsequent developments, the study is extended to a more complex structure that enhances system performance through appropriate approximation of the nonlinear functions of the considered model. It is worth mentioning that these approximations allow suitable model identification.

5.1. MLP neural network

MLP neural networks are relatively new classes of *ANNs* (Artificial Neural Network). Based on the universal approximation property of *MLP* network, nonlinear uncertain functions are estimated.

In this paper, we consider an input layer, a hidden layer (with four neurons) and an output layer. The general structure of the multi input/single output (*MISO*) of *MLP* network is shown in figure 2, where x is the input vector, $\hat{\varphi}_k$ (k=2, 4) is the approximation of the unknown nonlinear function, ϕ_{ki} is the sigmoid activation function of the i^{th} neuron (i=1,…,4), V_{ki} is the input weight vector related to the neuron i, x_p are the states (p=3,4), and W_k is the output weight vector:

$$V_{ki} = [V_{k?i}, ?V_{k\ \ i}, b_{ki}] \; ; \; W_k = [w_{k1}, w_{k2}, w_{k3}, w_{k4}]^T .$$

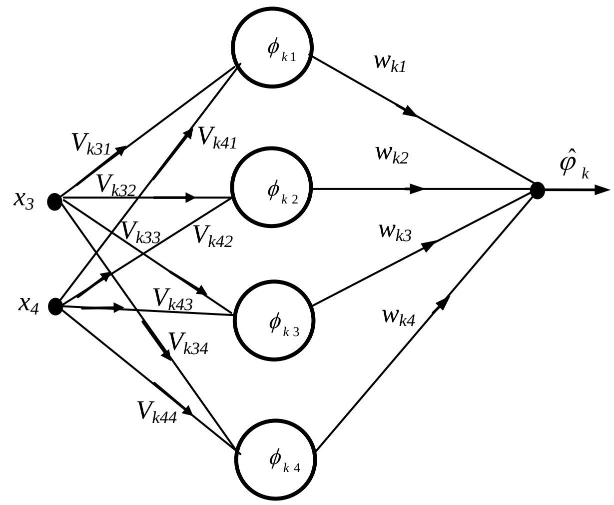


Figure 2. MLP Network Structure

From the network structure shown in Figure 2, the corresponding expression to the connection Input/Output can be described by:

$$\hat{\varphi}_k = \sum_{i=1}^{N} w_{ki}\phi_{ki}\left(\sum_{p=3}^{4}\left(V_{kpi}x_p + b_{ki}\right)\right) \tag{15}$$

where: N is the number of neurons in the hidden layer, b_{ki} is the bias of the neuron i.

The sigmoid activation function used in this case is given by the expression:

$$\phi(y) = \frac{1}{1+\exp(-\lambda y)} \quad , \quad \lambda > 0 \tag{16}$$

and its derivative is:

$$\dot{\phi}(y) = \lambda\phi(y)\left[1-\phi(y)\right] \tag{17}$$

5.2. Adaptive Control with Backstepping-MLP

The block diagram of the adaptive control is given in figure 3. The *MLP* network will approximate the nonlinear functions φ_2, φ_4 and estimate weights of the network.

The nonlinear function, which is approximated by the neural network, is defined by the following expression [14]:

$$\varphi(x) = W^T\phi\left(V^T\overline{x}\right) + \varepsilon(x) \tag{18}$$

where: $\varepsilon(x)$ is the approximation error, $\overline{x} = [x_3 \;\; x_4 \;\; 1]$ is the state vector augmented with a dummy node representing the bias input 1.

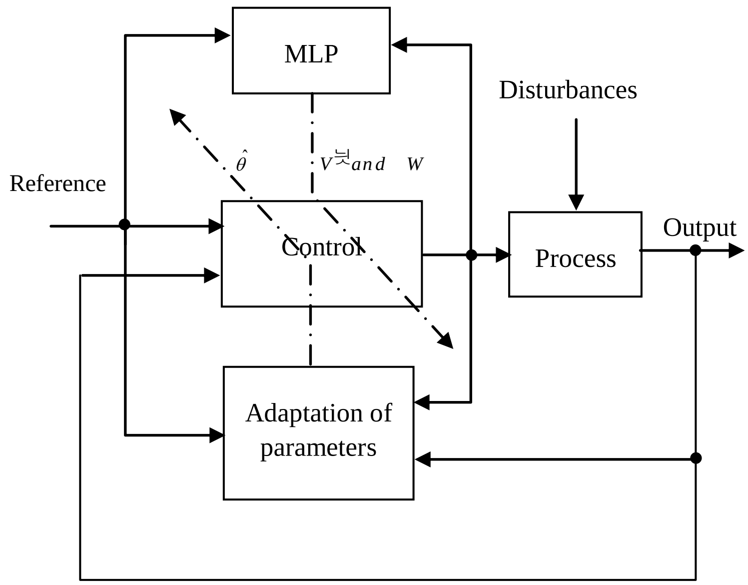


Figure 3. Neural Adaptive Control Diagram

To surpass the problems caused by the main drawbacks of standard backstepping control design, we propose to change equation (1) as follows:

$$\begin{cases} \dot{x}_1 = x_2 + \eta_1(x,\omega,t) \\ \dot{x}_2 = W_2^T\phi\left(V_2^T\bar{x}\right) + \varepsilon_2(x) - \dfrac{1}{\cos x_3}u + \eta_2(x,\omega,t) \\ \dot{x}_3 = x_4 + \eta_3(x,\omega,t) \\ \dot{x}_4 = W_4^T\phi\left(V_4^T\bar{x}\right) + \varepsilon_4(x) + \dfrac{1}{\ell}u + \eta_4(x,\omega,t) \end{cases} \tag{19}$$

For each function φ_k , the *MLP* network is chosen according to the desired approximation. This extension leads to the representation of the following system:

$$\begin{cases} \dot{x}_1 = x_2 + \eta_1(x,\omega,t) \\ \dot{x}_2 = \sum_{i=1}^{4} w_{2i}\phi_{2i}\left(\sum_{p=3}^{4}\left(V_{2pi}x_p + b_{2i}\right)\right) + \varepsilon_2(x) - \dfrac{1}{\cos x_3}u + \eta_2(x,\omega,t) \\ \dot{x}_3 = x_4 + \eta_3(x,\omega,t) \\ \dot{x}_4 = \sum_{i=1}^{4} w_{4i}\phi_{4i}\left(\sum_{p=3}^{4}\left(V_{4pi}x_p + b_{4i}\right)\right) + \varepsilon_4(x) + \dfrac{1}{\ell}u + \eta_4(x,\omega,t) \end{cases} \tag{20}$$

- **Step 1**

The procedure is the same as in expressions (3) to (7).

- **Step 2**

The last step will allow to deduce the control law. First, we define the relationship between a real value its estimation and the estimation error:

$$W = \hat{W} + \tilde{W}$$
$$V = \hat{V} + \tilde{V} \tag{21}$$

The second Lyapunov function is given by:

$$\vartheta_5 = \vartheta_3 + \frac{1}{2} z_4^{\ 2} + \frac{1}{2\gamma}\tilde{\beta}^2 + \frac{1}{2}\tilde{W}_4^T A^{-1}\tilde{W}_4 + \frac{1}{2}\tilde{V}_4^T B^{-1}\tilde{V}_4 \tag{22}$$

with A and B are two symmetrical constant matrices $A = A^T > 0$; $B = B^T > 0$.

From equations (7), (8), (19) and (22) the derivative of the Lyapunov function leads to:

$$\begin{aligned}\dot{\vartheta}_5 = & -c_3 z_3^{\ 2} - c_4 z_4^2 + z_4\left[z_3 + c_4 z_4 + W_4^T\phi\left(V_4^T\bar{x}\right) + \varepsilon_4(x) + \hat{\beta}u + \eta_4 - \dot{\alpha} - y_r^{(2)}\right] \\ & + \tilde{\beta}u + z_3(\eta_3 - h_3) - \frac{1}{\gamma}\tilde{\beta}\dot{\hat{\beta}} - \tilde{W}_4^T A^{-1}\dot{\hat{W}}_4 - \tilde{V}_4^T B^{-1}\dot{V}_4\end{aligned} \tag{23}$$

Using the Taylor development, we can write:

$$\phi\left(V_4^T\bar{x}\right) = \phi\left(\hat{V}_4^T\bar{x}\right) + \dot{\phi}\left(V_4^T\bar{x}\right)\tilde{V}_4^T\bar{x} + \mathrm{O}\left(\tilde{V}_4^T\bar{x}\right)^2 \tag{24}$$

where $\mathrm{O}\left(\tilde{V}_4^T\bar{x}\right)^2$ is the second order error and can be bounded. So, we can write the expression:

$$\begin{aligned}W_4^T\phi\left(V_4^T\bar{x}\right) &= W_4^T\left[\phi\left(\hat{V}_4^T\bar{x}\right) + \dot{\phi}\left(V_4^T\bar{x}\right)\tilde{V}_4^T\bar{x} + \mathrm{O}\left(\tilde{V}_4^T\bar{x}\right)^2\right] \\ &= \hat{W}_4^T\phi\left(V_4^T\bar{x}\right) + \tilde{W}_4^T\phi\left(\hat{V}_4^T\bar{x}\right) + W_4^T\dot{\phi}\left(\hat{V}_4^T\bar{x}\right)\tilde{V}_4^T\bar{x} + \tilde{W}_4^T\dot{\phi}\left(V_4^T\bar{x}\right)\tilde{V}_4^T\bar{x} + W_4^T\mathrm{O}\left(\tilde{V}_4^T\bar{x}\right)^2 \\ &= \hat{W}_4^T\phi\left(V_4^T\bar{x}\right) + \tilde{W}_4^T\phi\left(\hat{V}_4^T\bar{x}\right) + W_4^T\dot{\phi}\left(\hat{V}_4^T\bar{x}\right)\tilde{V}_4^T\bar{x} + \tilde{W}_4^T\dot{\phi}\left(V_4^T\bar{x}\right)V_4^T\bar{x} - \tilde{W}_4^T\dot{\phi}\left(\hat{V}_4^T\bar{x}\right)V_4^T\bar{x} + W_4^T\mathrm{O}\left(\tilde{V}_4^T\bar{x}\right)^2\end{aligned} \tag{25}$$

Equation (24) can be written as follows:

$$\begin{aligned}&\tilde{W}_4^T\dot{\phi}\left(\hat{V}_4^T\bar{x}\right)V_4^T\bar{x} + W_4^T\mathrm{O}\left(\tilde{V}_4^T\bar{x}\right)^2 \\ &= \tilde{W}_4^T\dot{\phi}\left(\hat{V}_4^T\bar{x}\right)V_4^T\bar{x} + W_4^T\phi\left(V_4^T\bar{x}\right) - W_4^T\phi\left(V_4^T\bar{x}\right) - W_4^T\dot{\phi}\left(\hat{V}_4^T\bar{x}\right)\tilde{V}_4^T\bar{x} \\ &= W_4^T.\left[\phi\left(V_4^T\bar{x}\right) - \phi\left(\hat{V}_4^T\bar{x}\right)\right] - W_4^T\dot{\phi}\left(V_4^T\bar{x}\right)\tilde{V}_4^T\bar{x} + \tilde{W}_4^T\dot{\phi}\left(\hat{V}_4^T\bar{x}\right)V_4^T\bar{x} \\ &= W_4^T.\left[\phi\left(V_4^T\bar{x}\right) - \phi\left(\hat{V}_4^T\bar{x}\right)\right] + W_4^T\dot{\phi}\left(V_4^T\bar{x}\right)\hat{V}_4^T\bar{x} - W_4^T\dot{\phi}\left(\hat{V}_4^T\bar{x}\right)V_4^T\bar{x}\end{aligned} \tag{26}$$

For the sigmoid activation function, continuous and differentiable on an interval, we can use the following limitation [14]:

$$\tilde{W}_4^T\dot{\phi}\left(\hat{V}_4^T\bar{x}\right)V_4^T\bar{x} + W_4^T\mathrm{O}\left(\tilde{V}_4^T\bar{x}\right)^2 \le \left\|W_4^T\right\|\left\|\dot{\phi}\left(V_4^T\bar{x}\right)\right\| + \left\|V_4\right\|_F\left\|\bar{x}\hat{W}_4^T\dot{\phi}\left(V_4^T\bar{x}\right)\right\|_F + \left|W_4^T\right|_1 \tag{27}$$

Using (23), (26) and (27), we can deduce the following control law:

$$u = -\hat{\ell}\left[z_3 + c_4 z_4 + \hat{W}_4^T \phi\left(V_4^T \bar{x}\right) + h_4 + v(t) - y_r^{(2)} \right] \quad (28)$$

where:

$$v(t) = k\left(\frac{1}{2} + \left\| \bar{x}\hat{W}_4^T \dot{\phi}\left(V_4^T \bar{x}\right)\right\|_F^2 + \left\| \dot{\phi}\left(\hat{V}_4^T \bar{x}\right) V_4^T \bar{x} \right\|^2 \right) z_4 + \varepsilon_{4M} \quad (29)$$

with : k is a positive value, $|\eta_4| \le h_4$ and $|\varepsilon_4(x)| \le \varepsilon_{4M}$.

Also, we can deduce the adaptation parameters and estimated weights:

$$\dot{\hat{\beta}} = \gamma z_4 u \quad ; \quad \dot{\hat{\ell}} = 1/(\gamma z_4 u) \quad (30)$$

$$\dot{\hat{W}}_4 = A\phi\left(V_4^T \bar{x}\right) z_4 - A\dot{\phi}\left(\hat{V}_4^T \bar{x}\right) V_4^T \bar{x} z_4 - \mu A \hat{W}_4$$
$$\dot{\hat{V}}_4 = B\bar{x} W_4^T \dot{\phi}\left(\hat{V}_4^T \bar{x}\right) z_4 - \mu B V_4 \quad (31)$$

where: γ and μ are positives values.

6. Simulation Results

This section shows simulation of the three studied control structures. The parameters of the considered pendulum are: $M=0.9$ *kg*, $m=0.1$ *kg*, $\ell=0.23m$, $g=9.81\ m/s^2$.

6.1. Non adaptive backstepping control results

The aim is to adjust the angle of the rod. The system being disturbed by sinusoid signals η_3 and η_4 respectively limited by $h_3=0.2$ and $h_4=0.7$. In this approach, the reference angle of the rod is equal to $\pi/6$. Adaptation gains are $c_3=c_4=10$.

Figures 4, 5 and 6 show respectively the inverted pendulum results of the output tracking, the control input and the tracking error.

Figure 4 shows that the output is perfectly tracked with a minor error (Figure 5) in the transient state. The corresponding input exhibits also a smooth behaviour (Figure 6).

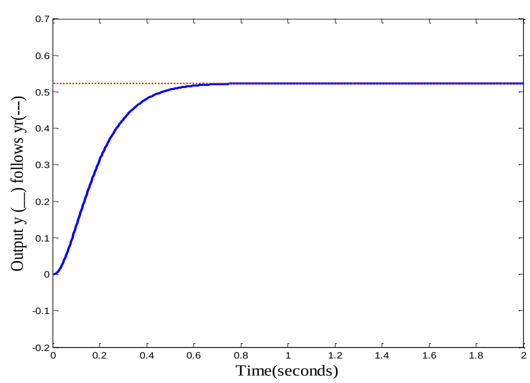


Figure 4. Desired and Obtained Output Tracking

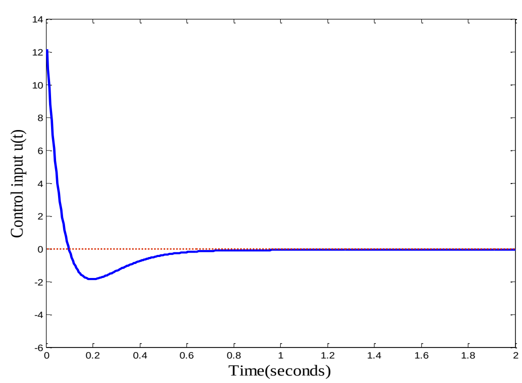


Figure 5. Non Adaptive Control Law

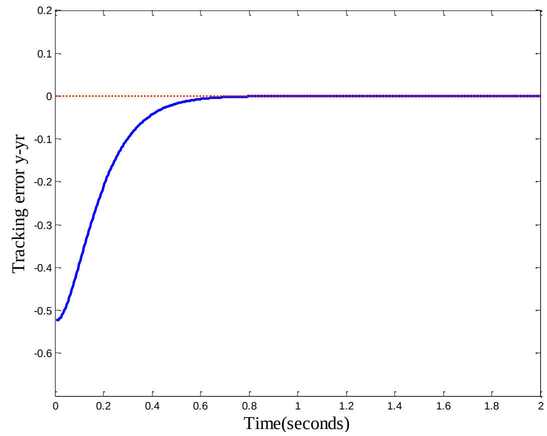


Figure 6. Non Adaptive Tracking Error

6.2. Adaptive Backstepping Control Results

In this case, the length of the rod is assumed unknown. The initial fixed value is $\ell=0.5m$ and the controller parameters are $c_3=c_4=10$, $\gamma=0.1$. The obtained results are depicted in Figures 7, 8 and 9.

The position reference of $\theta=\pi/6$ is perfectly tracked (Figure 7) and remains unaffected by the two sinusoidal disturbances. The corresponding tracking error in figure 8 is performed without an excessive peak and tends to zero in less than *0.6s*.

Figure 9 shows the force amplitude. This latter value is perfectly consistent with the considered system characteristics.

In Figure 10, the estimated length of the rod is compared with the exact one. A small transient state occurs before *0.2s* which is acceptable because of the inappropriate initialization value of the length ℓ (*0.5m vs. 0.23m*).

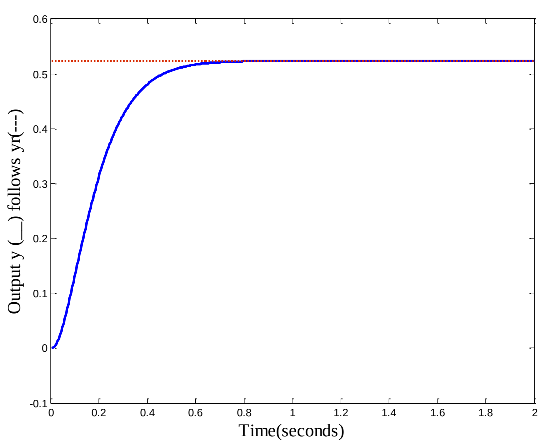


Figure 7. Desired and Obtained Output Tracking

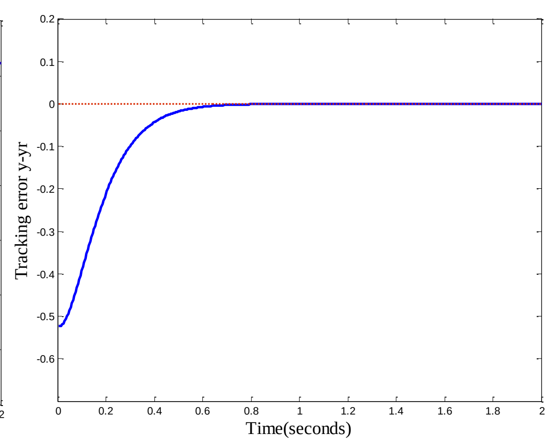
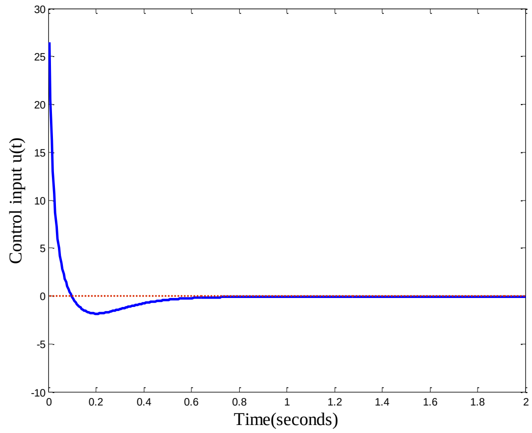


Figure 8. Adaptive Tracking Error



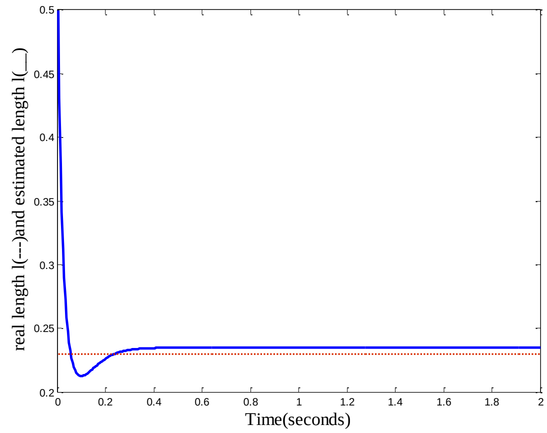


Figure 9. Adaptive Control Law **Figure 10. Estimation of the Parameter** ℓ

6.3. Neural Adaptive Backstepping Control Results

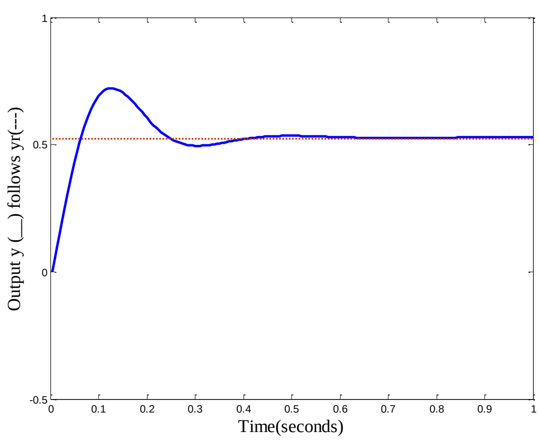
In this last simulation, the Lyapunov gains are fixed to $c_1=c_2=10$ and $\mu=10$. The network used contains three neurons in hidden layer and all the bias are also estimated with weights by neural backstepping techniques.

In this section, the performance of neural adaptive control law has verified by assuming that nonlinear functions are also unknown and this gives us the results represented by the following figures.

Figure 11 shows that the desired position is tracked in a very acceptable time. The time response is nearly *1s*; this is due to the estimation procedure of the unknown nonlinear functions of the model. The obtained input (Figure 12) is in within reasonable range. Figure 13 depicts the tracking error.

As for the rod length ℓ, Figure 14 shows the estimation of this parameter. It is obvious that this estimation is realized in a satisfactory manner.

Figures 15 and 16 show the estimated weights W_{41}, V_{131} and b_1.



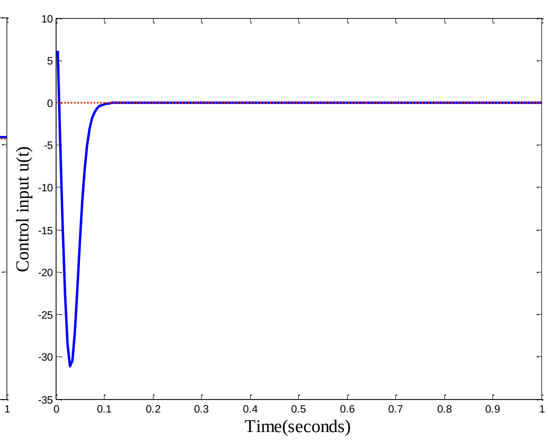


Figure 11. Desired and Obtained Output Tracking **Figure 12. Neural Adaptive Control Law**

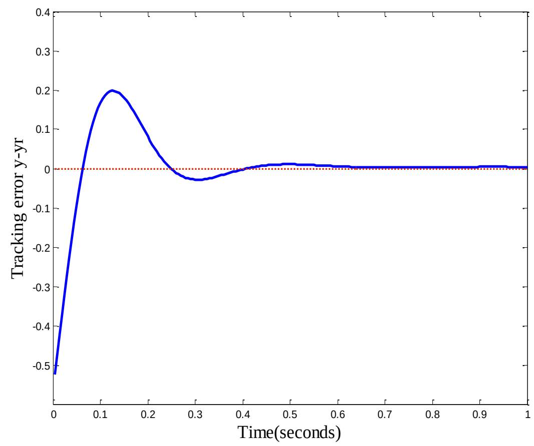


Figure 13. Neural Adaptive Tracking Error

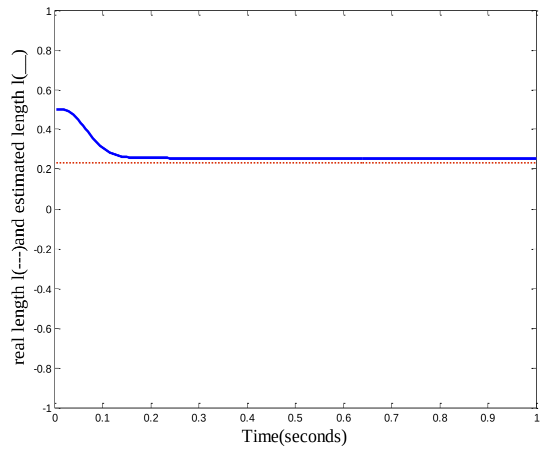


Figure 14. Estimation of the Parameter ℓ

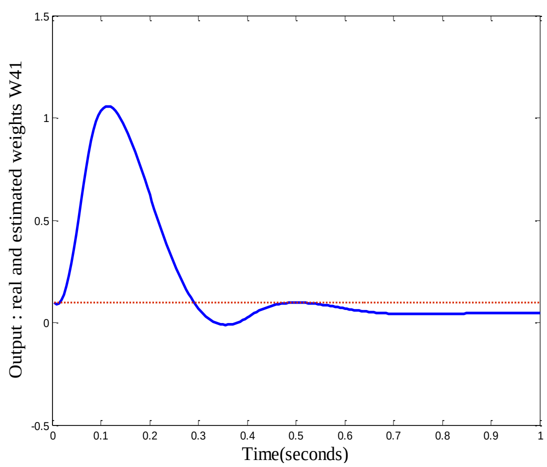


Figure 15. Estimated Weight w_{41}

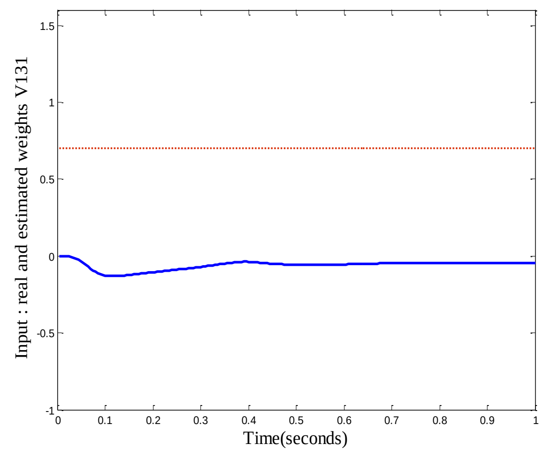


Figure 16. Estimated Weight V_{131}

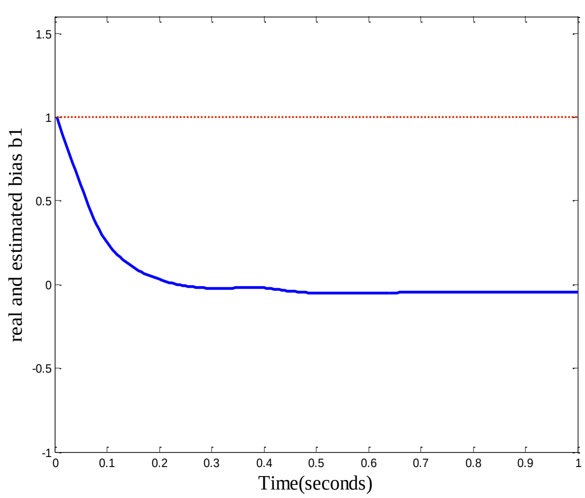


Figure 17. Estimated Bias b_1

7. Conclusion

In this paper, a neural adaptive backstepping controller applied to an inverted pendulum is synthesized. In the case of incomplete knowledge of the system, the adaptive backstepping based neural network is useful to improve system performance and to decrease the possible system instability. The use of neural network offers a great robustness against parameters uncertainties, time varying disturbances and unknown nonlinear functions.

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