Adaptive Neuro-Sliding Mode Control of PUMA 560 Robot Manipulator

Submitted: 28th June 2016; accepted: 7th October 2016

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DOI: 10.14313/JAMRIS_4-2016/27

Abstract:
The classical sliding mode control (SMC) is a robust control scheme widely used for dealing with nonlinear systems uncertainties and disturbances. However, the conventional SMC major drawback in real applications is the chattering phenomenon problem, which involves extremely high control activity due to the switched control input. To overcome this handicap, a pratical design method that combines an adaptive neural network and sliding mode control principles is proposed in this paper. The controller design is divided into two phases. First, the chattering phenomenon is removed by replacing the sign function included in the switched control by a continuous smooth function; basing on Lyapounov stability theorem. Then, an adaptive linear neural network, that has the role of online estimate the equivalent control in the neighborhood of the sliding manifold, is developed when the controlled plant is poorly modeled. Simulation results show clearly the satisfactory chattering free tracking performance of proposed controller when it is applied for the joints angular positions control of a 6-DOF PUMA 560 robot arm.

Keywords: *Puma 560, position control, NN, SMC, robustness, chattering*

1. Introduction

Robotic manipulators are highly nonlinear systems including high coupling dynamics. Moreover, uncertainties caused by link parameters imprecision, payload variations, unmodeled dynamics, such nonlinear friction and external disturbances etc. make the motion control of rigid manipulators very complicated task [1, 2]. Since sliding mode control is a strong tool for dealing with nonlinear systems, it has been widely used during the past decades in robotic systems control field.

The sliding mode control (SMC) design principle is based on the use of a high frequency switching control (corrective control) to drive and maintain the system states onto a particular surface expressed in the error space named sliding surface; this surface defines the closed loop desired behavior. After reaching the sliding surface, the controller turns the sliding phase on, and applies an equivalent control law to keep system states on this surface. The closed loop response becomes totally insensitive to external disturbances and model uncertainties.

However, the conventional SMC has some serious structural disadvantages that limit its implementation in real applications. The first drawback is the so-called chattering phenomenon, due to the switched control term that may excite high-frequency un modeled dynamics, and causes harmful effects to the controlled system (e.g. system instability, wear of the mechanism and actuators in mechanical systems) [3–5]. The second disadvantage is the equivalent control calculation difficulty when system modeling is very hard, or when system is subject to a wide range of parameters variation, or external disturbances [2, 6]. The most common used solutions for chattering reducing are the boundary layer approach, where a continuous approximation of the switched control is used instead of the sign function around the sliding surface. Nevertheless, the boundary layer thickness causes a trade-off relation between control performances and chattering elimination. The second main approach is the high order SMC; unfortunately the control design needs complex calculation procedure [6, 20].

In recent years, soft-computing methods such as artificial neural networks (NN) and fuzzy logic systems (FLS) have been successfully applied to overcome the practical problems met in the implementation of sliding mode controllers [1, 2, 6–17]. In the application of NN-based controllers to improve conventional SMC drawbacks, few main ideas were considered. The first one attempts to exploit NN learning capacities for online estimating the equivalent control or modeling errors [1, 2, 6, 11, 12], the neural net role's is then to compensate model nonlinear terms and disturbances effects; if this compensation term is sufficiently precise, the switched control, responsible of chattering phenomenon, goes to zero. The second idea tries to online determining the adequate switching control gain, just needed to overcome disturbances effects, for reducing the chattering phenomenon amplitude [13–17].

Among different approaches found in literature, this paper is interested to the algorithm developed by Y. Yildiz *et al.* in reference [11]. This choice is justified by the simplicity of design and the ease of practical implementation for this control algorithm based on strong mathematical foundations. Moreover, the closed loop system can achieve high tracking robustness while eliminating harmful effects of chattering phenomenon. The control synthesis was realized into two phases. First, the corrective control shape was adjusted to a continuous smooth function using

Lyapunov stability theorem; where the time derivative of Lyapunov candidate function was preselected to satisfy some particular quadratic form. Second, an adaptive linear neural network (ADALINE) was used to online estimate the equivalent control in the neighborhood of the sliding manifold through an adequate self-tuning mechanism to demonstrate the robust control performance of the proposed algorithm, several numerical simulations were applied for controlling joints angular positions of a PUMA 560 robot arm.

2. Controller Design

Consider the non linear system governed by the state space model:

$$\begin{cases} \dot{x} = f(x) + B(x)u + d(x,t) \\ y = [y_1, \dots, y_m]^T \end{cases} \quad (1)$$

where:
- $y \in \mathbb{R}^m$ denotes the output vector;
- $x = \left[y_1, \dot{y}_1, \cdots, y_1^{(r_1-1)}, \dots, y_m, \dot{y}_m, \cdots, y_m^{(r_m-1)}\right]^T \in \mathbb{R}^n$ is the state vector, with $\sum_{i=1}^{m} r_i = n$ is defined as the system relative degree;
- $f(x) \in \mathbb{R}^n$ is an unknown, continuous and bounded function;
- $B(x) \in \mathbb{R}^{n\times m}$ is the input matrix whose elements are continuous and bounded and, $rank(B(x)) = m$;
- $d(x,t) \in \mathbb{R}^n$ is an unknown, bounded disturbance.

Both $f(x)$ and $d(x, t)$ satisfy the matching conditions and all their components are bounded $|f_i(x)| \le M_i$ and $|d_i(x, t)| \le N_i$.

If assume that $y_d = [y_{1d}, \dots, y_{md}]^T$ represents the known desired trajectories, the control objective for system (1) is to eliminate the tracking error defined as:

$$e_t = \left[e_{t_1}, \dot{e}_{t_1}, \cdots, e_{t_1}^{(r_1-1)}, \dots, e_{t_m}, \dot{e}_{t_m}, \cdots, e_{t_m}^{(r_m-1)}\right]^T = x_d - x \quad (2)$$

where:

$$e_{t_i} = y_{id} - y_i \quad (3)$$

$$x_d = \left[y_{1d}, \dot{y}_{1d}, \cdots, y_{1d}^{(r_1-1)}, \dots, y_{md}, \dot{y}_{md}, \cdots, y_{md}^{(r_m-1)}\right]^T \quad (4)$$

For system (1), we define a set of sliding surfaces in the errors space as follows:

$$\sigma = \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \vdots \\ \sigma_m \end{bmatrix} = \begin{bmatrix} e_1^{(r_1-1)} + \alpha_{11} e_1^{(r_1-2)} + \cdots + \alpha_{1\,(r_1-1)} e_1 \\ e_2^{(r_2-1)} + \alpha_{21} e_2^{(r_2-2)} + \cdots + \alpha_{2\,(r_2-1)} e_2 \\ \vdots \\ e_m^{(r_m-1)} + \alpha_{m1} e_m^{(r_m-2)} + \cdots + \alpha_{m\,(r_m-1)} e_m \end{bmatrix}$$

$$\sigma = G \cdot e_t = 0 \quad (5)$$

where, $G \in \mathbb{R}^{m\times n}$, and $\sigma_i(e_i) = e_i^{(r_i-1)} + \alpha_{i1} e_i^{(r_i-2)} + \cdots + \alpha_{i(r_i-1)} e_i$ have multiple negative real roots.

To remove chattering, let us choose the following Lyapunov candidate function

$$V = \tfrac{1}{2}\sigma^T \sigma. \quad (6)$$

To make the time derivative of (6) negative definite and satisfies some preselected form, we have to find the adequate control input. Equating the time derivative of this Lyapunov function to a negative definite function of the form,

$$\dot{V} = -\sigma^T D \sigma \quad (7)$$

where, $D \in \mathbb{R}^{m\times m}$ is chosen positive definite symmetric matrix to satisfy Lyapunov conditions.

Now, taking the time derivative of (6) and replacing it into (7), the following requirement is found,

$$\sigma^T(\dot{\sigma} + D\sigma) = 0 \quad (8)$$

For $\sigma \neq 0$, the control vector must satisfies the condition given by the equation below:

$$(\dot{\sigma} + D\sigma) = \left[G\left(\dot{x}_d - f(x) - B(x)u - d(x,t)\right) + D\sigma\right] = 0 \quad (9)$$

Finally, the control that satisfies the sliding mode conditions is given by

$$u = -(GB)^{-1}(G(f + d - \dot{x}_d) - D\sigma) = u_{eq} + (GB)^{-1} D\sigma \quad (10)$$

It is clear that the control law does not contain any discontinuous term. Therefore, the chattering phenomenon is perfectly eliminated. However, the so-called equivalent control u_{eq} is unknown since f and d are unknown and not measurable. Therefore, it will be estimated using an ADALINE neural network presented in Figure below,

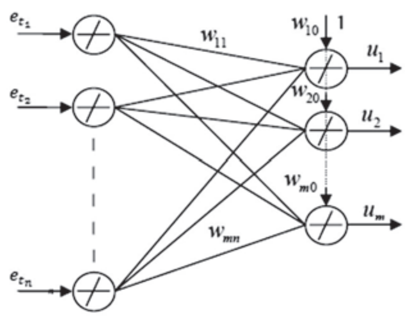

Fig. 1. Proposed Neural Network scheme

$$u_i = \sum_{j=1}^{n} e_{t_j} w_{ij} + 1 w_{i0}, \; i = 1, \cdots, m \quad (11)$$

where, e_{t_j} is the j^{th} row of e_t, and the w_{ij} refer to network weights.

The adaptation mechanism is chosen by finding the neural network that minimize the error function cost

(12), that satisfies the requirement (9) determined from the Lyapunov stability conditions,

$$E = \frac{1}{2}(\dot{\sigma} + D\sigma)^T(\dot{\sigma} + D\sigma). \qquad (12)$$

Due the simplicity of the selected NN structure, the on-line learning procedure can easily be calculated using the simple back propagation gradient descent algorithm (13) and (14). The existence and the stability of the global minima, and the stability of the sliding manifold when error function minima are reached; were proven in [11]:

$$\dot{w}_{ij} = -\eta\frac{\partial E}{\partial w_{ij}} = -\eta\frac{\partial E}{\partial u_i}\frac{\partial u_i}{\partial w_{ij}}$$
$$= \eta(\dot{\sigma} + D\sigma)^T GB_i(x)e_{t_j} \qquad (13)$$

where, $B_i(x)$ is the i^{th} column of the matrix $B(x)$.

For the bias terms w_{i0}, the weight update can be computed using the same procedure,

$$\dot{w}_{i0} = -\eta\frac{\partial E}{\partial w_{ij}} = \eta(\dot{\sigma} + D\sigma)^T GB_i(x). \qquad (14)$$

Notice that the control design does not require the knowledge of vectors f and d. So, from control point of view, they can be considered as unknown functions satisfying some particular conditions as mentioned above.

3. Robot Manipulator Mathematical Model

The PUMA 560 manipulator, Figure 2, powered by DC motors is modeled by the following non linear dynamic system [18, 19, 21],

$$\begin{cases} M(q)\ddot{q} + B'(q)[\dot{q}\dot{q}] + C(q)[\dot{q}^2] + \\ \quad +G'(q) = N(\tau_m - \tau_f) \\ L_a\dot{I} + R_aI + K_eN\dot{q} = V \\ \tau_m = K_mI \end{cases} \qquad (15)$$

where, $\tau_m \in \mathbb{R}^{6\times1}$ denotes actuators torques vector, $\tau_f \in \mathbb{R}^{6\times1}$ actuators friction torques, $q, \dot{q},$ and $\ddot{q}$ denote joints angular positions, velocities and accelerations vectors. Symbols $[\dot{q}\dot{q}]$ and $[\dot{q}^2]$ are notation for the $n(n{-}l)/2$-vector of velocity products and the n-vector of squared velocities. $[\dot{q}\dot{q}]$ and $[\dot{q}^2]$ are given by:

$$[\dot{q}\dot{q}] = [\dot{q}_1\dot{q}_2, \dot{q}_1\dot{q}_3 \cdots, \dot{q}_1\dot{q}_n, \dot{q}_2\dot{q}_3, , \cdots, \dot{q}_{n-2}\dot{q}_n, \dot{q}_{n-1}\dot{q}_n]^T$$

$$[\dot{q}^2] = [\dot{q}_1^2, \dot{q}_2^2, \cdots, \dot{q}_n^2]^T.$$

$M(q) \in \mathbb{R}^{6\times6}$ is the inertia matrix, $B'(q) \in \mathbb{R}^{6\times15}$ the Coriolis torques matrix, $C(q) \in \mathbb{R}^{6\times6}$ the centrifugal torques matrix, and $G'(q) \in \mathbb{R}^{6\times1}$ the gravity torques vector. $L_a \in \mathbb{R}^{6\times6}$ and $R_a \in \mathbb{R}^{6\times6}$ are, respectively, the armature windings inductance and resistance diagonal matrices, $I \in \mathbb{R}^{6\times1}$ is the armature current vector, $V \in \mathbb{R}^{6\times1}$ denotes the actuators control voltage, $N \in \mathbb{R}^{6\times6}$ gears ratios diagonal matrix, $K_e \in \mathbb{R}^{6\times6}$ is the back e.m.f constants diagonal matrix, and $K_m \in \mathbb{R}^{6\times6}$ is the motors torques constants diagonal matrix.

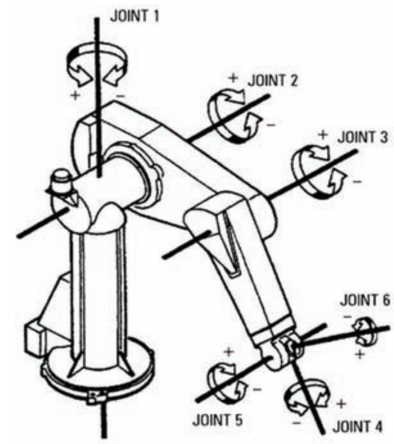

Fig. 2. PUMA 560 robot manipulator

In order to facilitate the control task, we propose to simplify (15) by neglecting the inductances of the actuators armatures. Then, currents vector expression becomes:

$$I = R_a^{-1}[V - K_eN\dot{q}] \qquad (16)$$

Finally, system (15) is reduced to:

$$M(q)\ddot{q} + h(q, \dot{q}) = KV \qquad (17)$$

where,

$$\begin{cases} h(q, \dot{q}) = B'(q)[\dot{q}\dot{q}] + C(q)[\dot{q}^2] + G'(q) + \\ \quad +N\cdot K_m\cdot R_a^{-1}\cdot K_eN\dot{q} + N\tau_f \\ K = N\cdot K_m\cdot R_a^{-1} \end{cases} \qquad (18)$$

Friction is frequently modeled as [21],

$$\tau_{f_i} = \mathrm{B}_i^*\dot{q}_i + \tau_{\mathrm{C_i}} \qquad (19)$$

where, $(B_i^*\dot{q}_i)$ is the viscous friction, and τ_{C} denotes Coulomb friction,

$$\tau_{C_i} = \begin{cases} 0 \ \text{ if } \dot{q}_i = 0 \\ \tau_{C_i}^+ \text{ if } \dot{q}_i > 0 \\ \tau_{C_i}^- \text{ if } \dot{q}_i < 0 \end{cases} \qquad (20)$$

To write system (17) in the form (1), choosing the following state vector x,

$$x = [q_1, \dot{q}_1, q_2, \dot{q}_2, \dots, q_6, \dot{q}_6]^T \qquad (21)$$

The output vector is defined as,

$$y = [q_1, q_2, \dots, q_6]^T \in \mathbb{R}^{6\times1}. \tag{22}$$

The input vector is,

$$u = V \tag{23}$$

where: $|V_i|_{max} = 40\ volt$ [21].

Hence, dynamic model (17) can be rewritten in the state space form (1). Where,

$$f(x) = [x_2, F_1(x), x_4, F_2(x), \dots, x_{12}, F_6(x)]^T \in \mathbb{R}^{12\times1} \tag{24}$$

$F_i(x)$ is the i^{th} row of the $F(x) \in \mathbb{R}^{6\times1}$ vector defined as,

$$F(x) = -M^{-1}(x)h(x) \tag{25}$$

$$B(x) = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ H_{11} & H_{12} & \cdots & H_{16} \\ 0 & 0 & \cdots & 0 \\ H_{21} & H_{22} & \cdots & H_{26} \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 \\ H_{61} & H_{62} & \cdots & H_{66} \end{bmatrix} \in \mathbb{R}^{12\times6} \tag{26}$$

where, $H_{ij}(x)$ are the elements of the $H(x) \in \mathbb{R}^{6\times6}$ matrix defined as:

$$H(x) = M^{-1}(x)K. \tag{27}$$

For checking the robustness of the controller, disturbance torques $d_i(t)$ introduced in [19] are considered,

$$d(t) = [0, d_2(t), 0, d_4(t), \dots, 0, d_{12}(t)]^T \in \mathbb{R}^{12\times1} \tag{28}$$

where:

$$d_i(t) = 7.5\sin(4.3575t) + 3.5\sin(9.825) + 3.5\sin(2.7075) - 4.5. \tag{29}$$

The proposed controller block scheme applied for the position control of 6-DOF PUMA 560 robot arm is given by the figure below.

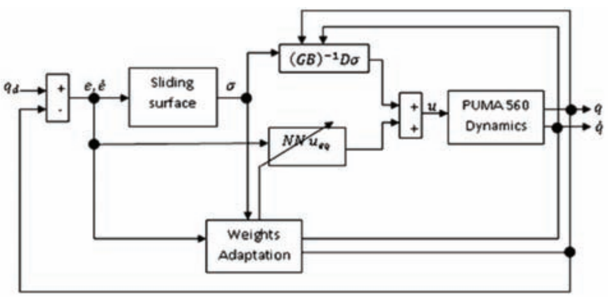

Fig. 3. The proposed adaptive neuro sliding mode control bloc scheme

4. Simulation Results

Here, the proposed neuro-sliding mode controller applied for the position control of 6-DOF PUMA 560 robot arm, is tested by numerical simulations using Matlab/Simulink.

First, robot is controlled in joint space for a point to point motion using elliptic trajectories [22] as reference inputs. Then, control results in operational space (Cartesian space) are shown using kinematic models presented in [19].

In order to test the robustness and the chattering rejection, wide parameters uncertainties $\Delta M = 10\%\widehat{M}(q)$, $\Delta h = 10\%\hat{h}(q)$ were introduced into the manipulator nominal model ($\widehat{M}, \hat{h}$ are nominal values of M, h); and a comparison with the conventional sliding mode control were performed. The classical SMC control law is defined as:

$$u_{SMC} = u_{eq} + u_{disc}$$

where,

$$u_{eq} = K^{-1}\widehat{M}\left(\widehat{M}^{-1}\hat{h} + \ddot{q}_d(t) + \Lambda\dot{e}(t)\right)$$

$$u_{disc} = -K' sign(\sigma(x,t))$$

$$e = q_d(t) - q(t)$$

$$\sigma(x,t) = \dot{e}(t) + \Lambda e(t)$$

$$\Lambda = dig(\Lambda_1, \dots, \Lambda_6), K' = diag\left(K'_1, \cdots K'_6\right)$$

$$sign\left(\sigma(x,t)\right) = [sign(\sigma_1) \cdots sign(\sigma_6)]^T,$$

$$\Lambda_i > 0,\ K'_i > 0. \tag{30}$$

The obtained results using the 4th order Runge Kutta solver with fixed step time $\Delta t = 0.001$ are shown below.

Reference trajectories in both joint space and operational space are defined as,

1. Joint space reference signals,

$$q_i(t) = \frac{(q_{fi} - q_{0i})}{2}\left(1 - \frac{\cos\frac{\pi(t-t_0)}{T}}{\sqrt{1 - \alpha\sin^2\frac{\pi(t-t_0)}{T}}}\right) + q_{0i}$$

$$0 < \alpha < 1 \tag{31}$$

2. Operational space reference signals,

The parametric representation of the Butterfly trajectory defined in [19] in x-y plane is given by,

$$\begin{cases} x'_d = 0.02\cos(t)\left(e^{\cos(t)} - 2\cos(4t) - \sin^5\left(\frac{t}{12}\right)\right) + 0.35 \\ y'_d = 0.02\sin(t)\left(e^{\cos(t)} - 2\cos(4t) - \sin^5\left(\frac{t}{12}\right)\right) + 0.2 \\ z_d = 0.4326 \end{cases} \tag{32}$$

Notice that wrist joints q_4, q_5, and q_6 were kept to zero.

1. Joint space control:

1.1. Nominal model control without disturbance:

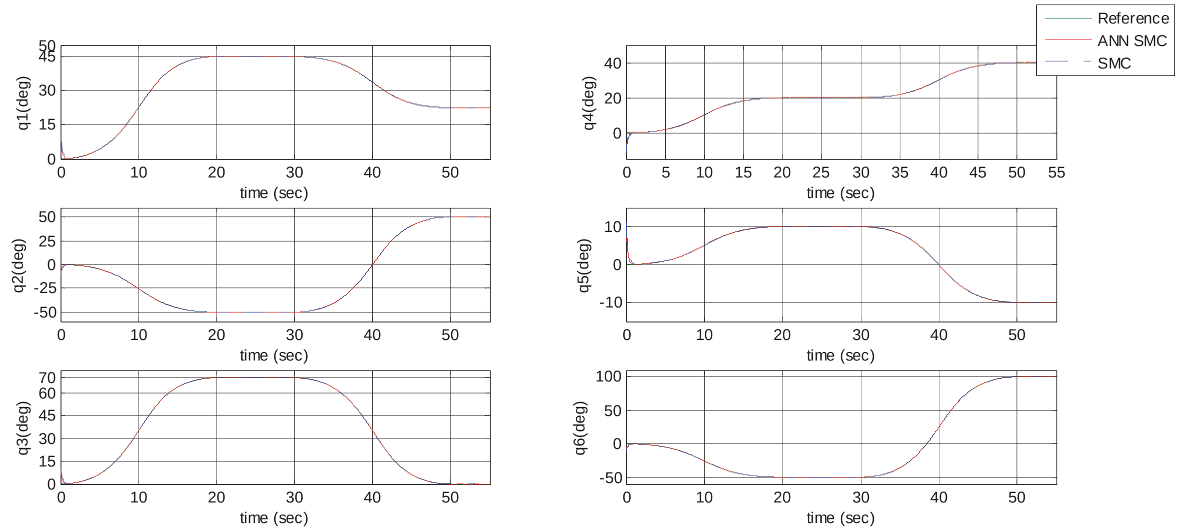

Fig. 4. Desired positions tracking for nominal model

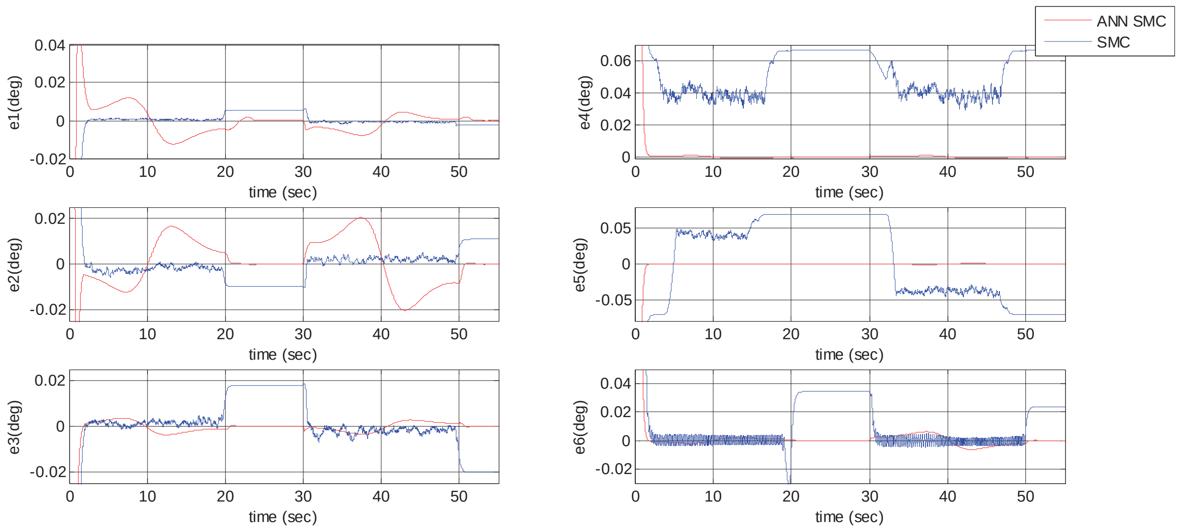

Fig. 5. Tracking errors for nominal model

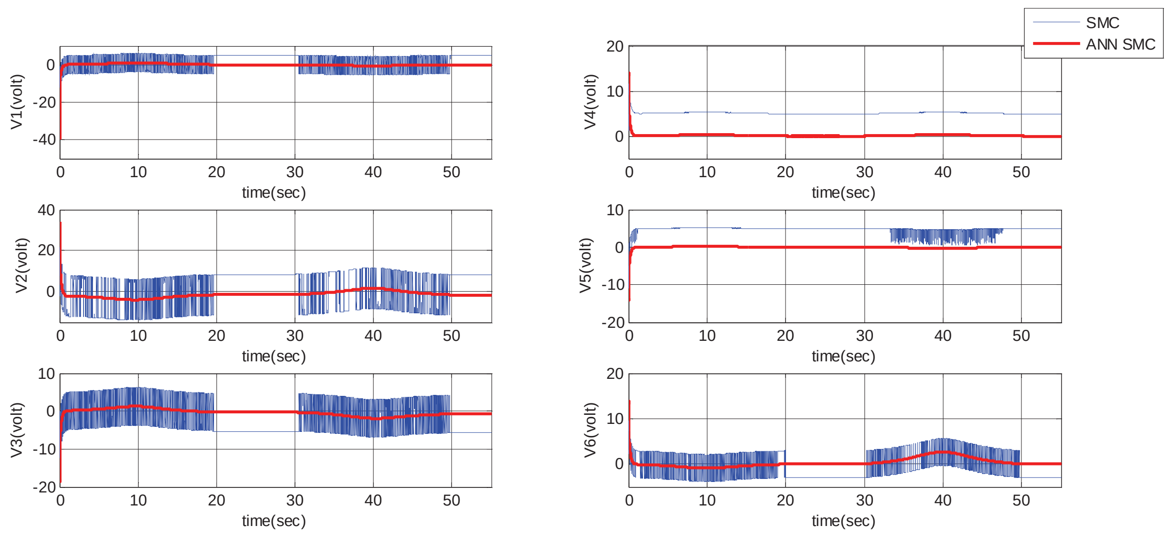

Fig. 6. Control inputs for nominal model

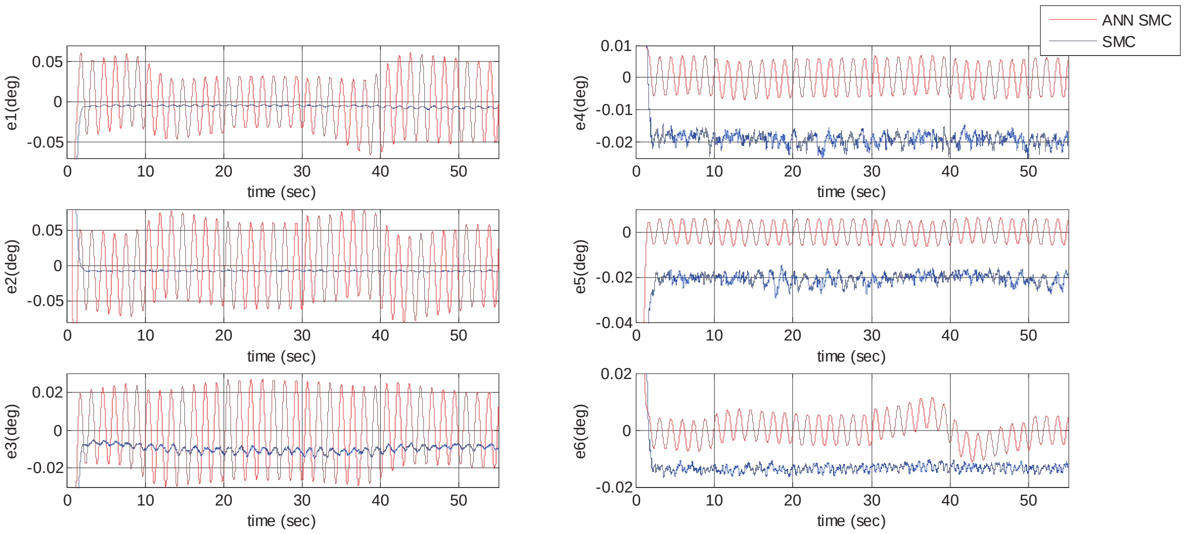

Fig. 7. Tracking errors for uncertain model with disturbance

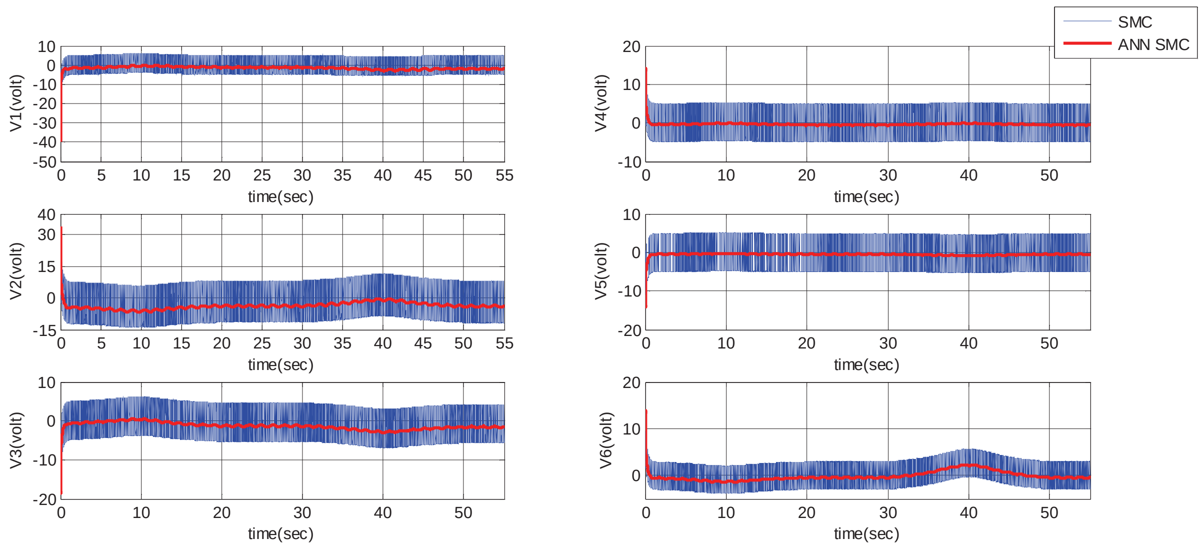

Fig. 8. Control inputs for uncertain model with disturbance

2. Operational space control:

2.1. Nominal model without disturbance:

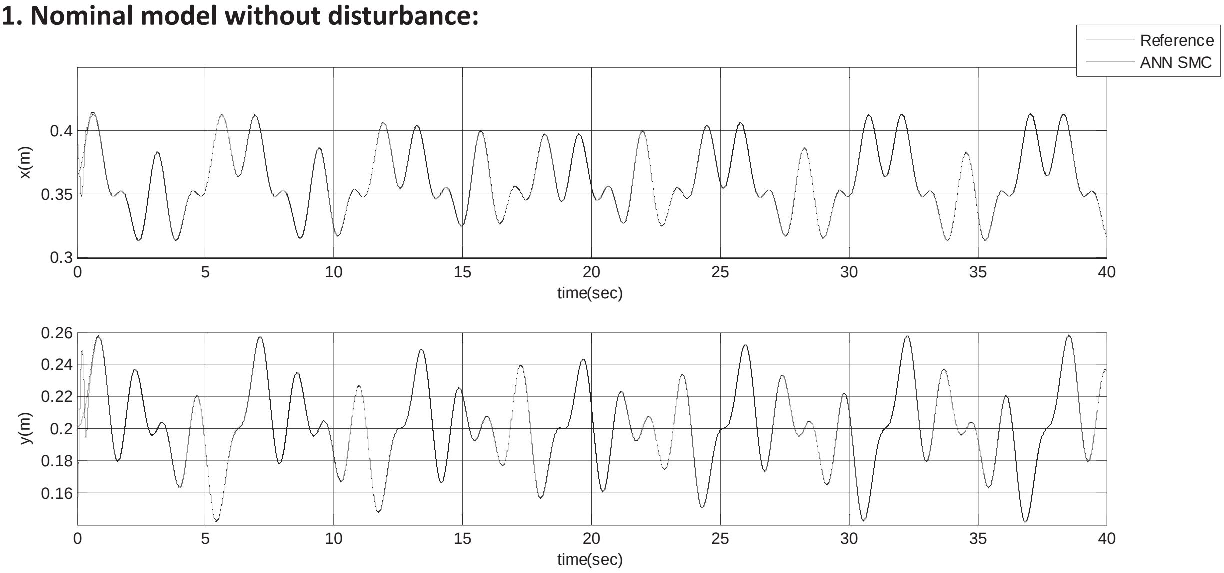

Fig. 9. Desired position tracking for nominal model

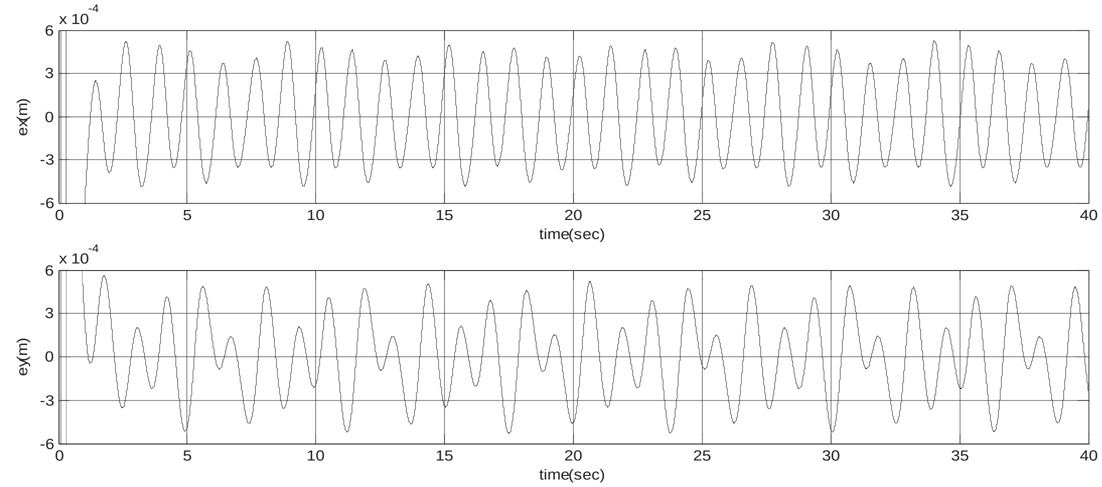

Fig. 10. Tracking errors for nominal model

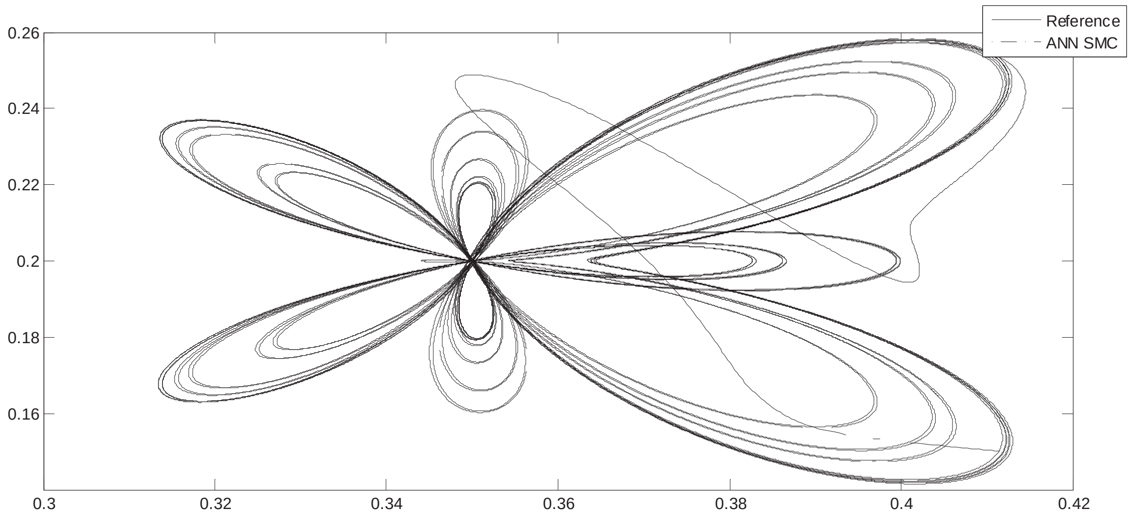

Fig. 11. Desired and actual output butterfly trajectory for nominal model

2.2. Uncertain model with disturbance:

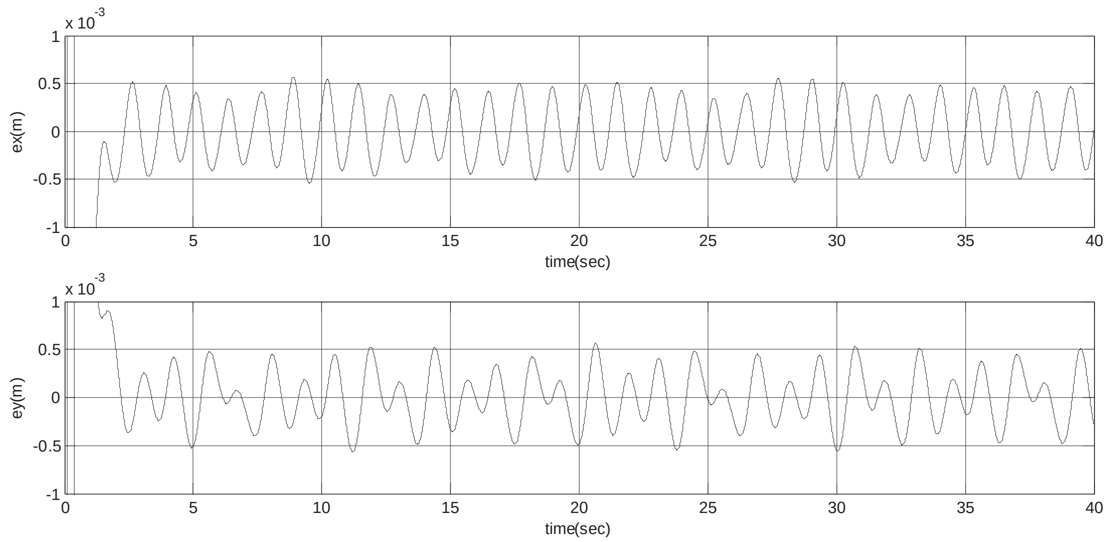

Fig. 12. Tracking errors for uncertain model with disturbance

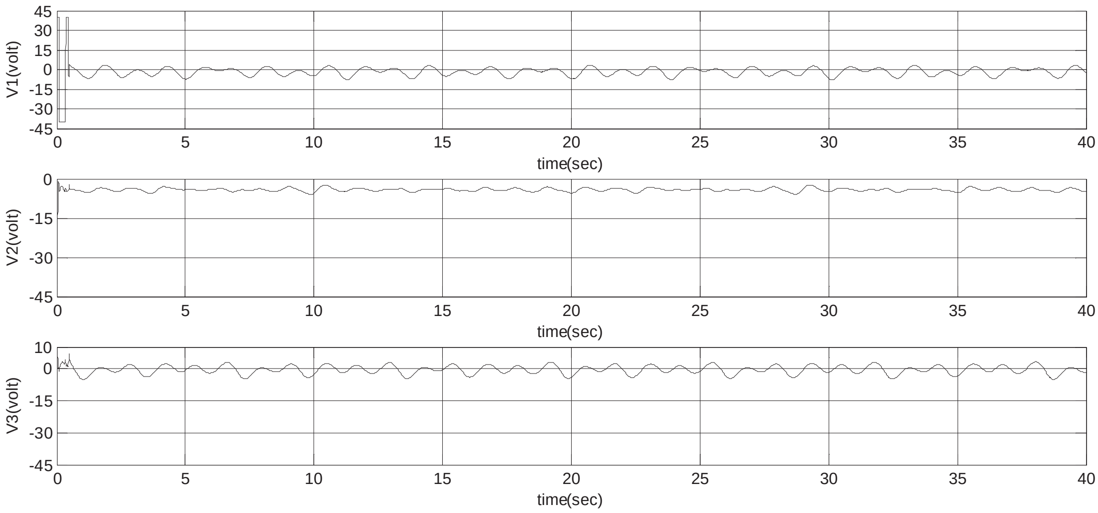

Fig. 13. Control inputs for uncertain model with disturbance

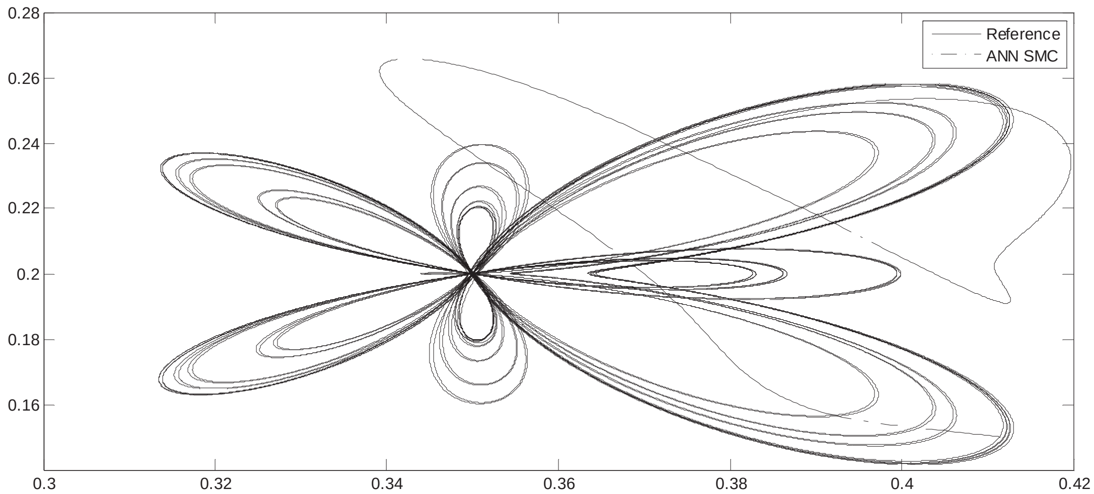

Fig. 14. Desired and actual output butterfly trajectory for uncertain model with disturbance

The comparison between nominal and uncertain models, Figures 5, 7 and figures 10, 12; shows that the tracking errors remain limited near zero. Therefore, we can conclude the satisfactory robustness of the proposed controller tracking performance against disturbances effects and modeling errors (parametric uncertainties and neglected actuators dynamics).

Figures 6 and 8 compare the control inputs between adaptive NN SMC and conventional sliding mode control. It is obvious that the harmful effects of the chattering phenomenon are completely removed by the proposed control voltage. Therefore, this solution improves significantly the conventional sliding mode control qualities in pratical implimentations. In addition, we observe that the proposed control magnitudes are much lower, which leads to a smaller control energy.

As conclusion, simulation results confirm that the best compromise between tracking performance robustness and chattering elimination is ensured by the proposed adaptive NN sliding mode controller.

5. Conclusion

In this paper, an adaptive neural network controller based on sliding mode control has been successfully applied for PUMA 560 robot arm robust trajectory tracking.

The simulation results show that the adaptive NN sliding mode controller can achieve very satisfactory chattering-free trajectory tracking performance compared to conventional SMC. In addition, the magnitude of control inputs were smaller than that of the classical scheme; which makes the energy efficiency better.

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