

Neuro-sliding Mode Control for Robot Manipulators

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Abstract: This paper presents a neuro-sliding mode control method for a robot manipulator. The sliding mode controller requires to identify robot models to lessen the work of the controller although it can be used as a non model-based nonlinear controller. Selection of the gain for the nonlinear function becomes important and affects the performance. To make it easy of selecting the gain, a neural network is used to compensate for the modeling error to form a neuro-sliding control method. Stability analysis for the neuro-sliding control method is provided. Simulation studies of controlling joints of the three-link robot manipulator are presented.

Keywords: neuro-sliding mode control, robot manipulator, stability

1. INTRODUCTION

Control of robot manipulators becomes a classical control problem nowadays since other robots are getting more attention from researchers. Although mobile robots are gaining popularity due to the mobility, manipulators are also required for robots to perform manipulation tasks.

Therefore, manipulation control of robots is classical, but still primary in robot technologies and applications. There have been many control algorithms for controlling robot manipulators. Model-based feedback control, known as a computed torque control method is one of main model-based control schemes. Advanced control techniques such as disturbance observer-based control methods and adaptive control methods, have been well developed and formulated [1, 2].

However, aforementioned control methods require robot dynamic models which have always errors and other unmodeled dynamics are ignored. Thus, it is easier to use non-model based control methods for controlling robots. Well known non-model based control methods include PID control schemes. However, PID control schemes suffer from poor performances owing to the nonlinearity of the robot.

One of promising non-model based control schemes is to use intelligent techniques. Major intelligent non model-based control schemes include neural network control and fuzzy control [3-5]. Learning ability of neural network is quite an attractive skill for controlling robots. Transferring human skills to machines by fuzzy logic is also an attractive skill for robots.

In a meanwhile, one of nonlinear control schemes of not requiring robot dynamic models is a sliding mode control (SMC) scheme. SMC is simple and powerful that it has been used in various motion control applications. One of the advantages of SMC is that the stability of the controlled system is guaranteed in the Lyapunov sense for either model-based or non-model based scheme [6-10].

Performance of non model-based SMC depends upon

the appropriate selection of nonlinear gains, which requires time consuming. The nonlinear gain has to deal with the whole robot dynamics which is usually unknown and time varying. To deal with the problem of uncertainties of modeling errors, neural network is used [9, 10] and fuzzy logic is used in the framework of the sliding model control [11].

In this paper, a RBF-like neural network is used to estimate the robot dynamics in the configuration of the sliding mode control. Combination of SMC and neural network forms the neuro-SMC structure. Stability of the neuro-SMC is derived on the basis of Lyapunov criteria.

Simulation studies of tracking joint trajectories are performed for three-link robot manipulators. The robot is required to follow the desired trajectory under the presence of joint frictions. Tracking performances between the SMC and neuro-SMC are compared.

2. ROBOT MANIPULATOR DYNAMICS

The robot manipulator dynamics is give as

$$D(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) = \tau \quad (1)$$

where $D(q)$ is an $n \times n$ inertia matrix, $C(q, \dot{q})\dot{q}$ is an $n \times 1$ Coriolis and centrifugal force vector, $G(q)$ is an $n \times 1$ Gravity force vector, and q, \dot{q}, \ddot{q} are an $n \times 1$ joint angle, joint velocity, joint acceleration vector, respectively.

$$e = q_d - q \quad (2)$$

where q_d is the desired joint trajectory.

Assume that the sliding error surface is defined as

$$s = \dot{e} + \lambda e, \dot{s} = \ddot{e} + \lambda \dot{e} \quad (3)$$

$$\dot{q} = \dot{q}_d - s + \lambda e, \ddot{q} = \ddot{q}_d - \dot{s} + \lambda \dot{e}$$

where λ is the constant gain.

Substituting (3) into (1) yields the modified dynamics equation

$$D\dot{s} = f(q, \dot{q}) - Cs - \tau \quad (4)$$

where $f(q, \dot{q}) = D(\ddot{q}_d + \lambda\dot{e}) + C(\dot{q}_d + \lambda e) + G$.

3. SLIDING MODE CONTROL

The sliding mode control is a well known nonlinear control method. The error surface is defined for the control input to push states to the surface.

The Lyapunov function is defined as

$$V = \frac{1}{2} s^T Ds \quad (5)$$

Differentiating the Lyapunov function V yields

$$\dot{V} = \frac{1}{2} s^T \dot{D}s + s^T D\dot{s} \quad (6)$$

Substituting $D\dot{s}$ in (4) into (6) yields

$$\begin{aligned} \dot{V} &= \frac{1}{2} s^T \dot{D}s + s^T (f - Cs - \tau) \\ &= \frac{1}{2} s^T (\dot{D} - 2C)s + s^T (f - \tau) \end{aligned} \quad (7)$$

Since the skew symmetry of $\dot{D} - 2C = 0$ (7) becomes

$$\dot{V} = s^T (f - \tau) \quad (8)$$

Selecting the model-based control law as

$$\begin{aligned} \tau &= \tau_{eq} + \tau_{smc} \\ &= \hat{D}(\dot{q}_d + \lambda\dot{e}) + \hat{C}(\dot{q}_d + \lambda e) + \hat{G} + K \operatorname{sgn}(s) \end{aligned} \quad (9)$$

where K is a positive gain matrix.

Substituting (9) into (8) yields

$$\dot{V} = s^T (\Delta f - K \operatorname{sgn}(s)) \quad (10)$$

where $\Delta f = \Delta D(\dot{q}_d + \lambda\dot{e}) + \Delta C(\dot{q}_d + \lambda e) + \Delta G$ and

$$\Delta D = D - \hat{D}, \Delta C = C - \hat{C}, \Delta G = G - \hat{G}.$$

If the estimated model is correct, then $\Delta f = 0$ leads to the stability as.

$$\dot{V} = -s^T K \operatorname{sgn}(s) = -K |s| < 0 \quad (11)$$

It satisfies the Lyapunov stability condition. However,

there are always the modeling errors. Then we have the following condition to be satisfied.

$$\|K\| > \|\Delta f\| \quad (12)$$

which may cause a larger chattering behavior.

The gain K can be selected to satisfy the equation (12) depending upon the magnitude of Δf for the stability, but we still have the inherent chattering problem. Therefore, neural network is introduced to compensate for the robot manipulator model, Δf so that equation (11) is satisfied.

4. NEURO-SLIDING MODE CONTROL

4.1 RBF-like neural network

Radial basis function has the linear output that can be described as

$$\hat{f} = \hat{W}^T \phi(x) + \varepsilon \quad (13)$$

where \hat{W} is the weight, $\phi(q)$ is the output of the hidden layer and ε is the approximation error. The universal approximation theorem tells us that the modeling error of RBF is defined as

$$\begin{aligned} \varepsilon &= f - \hat{f} = W^T \phi(x) - \hat{W}^T \phi(x) \\ &= \tilde{W}^T \phi(x) \end{aligned} \quad (14)$$

where $\tilde{W} = W^T - \hat{W}^T$.

The weight update law is defined as

$$\dot{\hat{W}}^T = \eta \phi(x) s^T \quad (15)$$

where η is the learning rate.

4.2 Neuro-sliding mode control

A RBF-like neural network is added to the sliding mode control for the non model-based system as shown in Fig. 1. The control input torque is given as

$$\tau = \tau_c + \tau_N \quad (16)$$

Neural network can approximate any nonlinear functions based on the universal approximation theorem.

$$\tau_N = \hat{f} = \hat{W}^T \phi(x) + \varepsilon \quad (17)$$

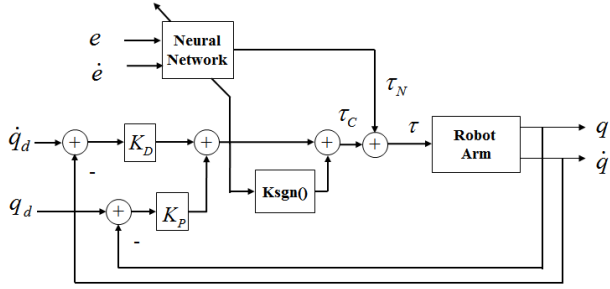


Fig. 1 Neuro-sliding mode control block diagram

4.3 Stability analysis

Lyapunov function is defined as

$$V = \frac{1}{2} s^T D s + \frac{1}{2\eta} \tilde{W}^T \tilde{W} \tag{18}$$

Differentiating (18) and substituting (16) yields

$$\dot{V} = s^T (f - \tau) + \frac{1}{\eta} \tilde{W}^T \dot{\tilde{W}} \tag{19}$$

The control law is given as (16) and substituting it into (19) yields

$$\begin{aligned} \dot{V} &= s^T (W^T \phi(x) - \hat{W}^T \phi(x) - \varepsilon - K \operatorname{sgn}(s)) + \frac{1}{\eta} \tilde{W}^T (-\dot{\hat{W}}) \\ &= s^T (\tilde{W}^T \phi(x) - \varepsilon - K \operatorname{sgn}(s)) + \frac{1}{\eta} \tilde{W}^T (-\dot{\hat{W}}) \\ &= \tilde{W}^T (\phi(x) s^T - \frac{1}{\eta} \dot{\hat{W}}) - K |s| - s^T \varepsilon \end{aligned} \tag{20}$$

Substituting the weight update law in (15) into (20) yields

$$\begin{aligned} \dot{V} &= \tilde{W}^T (\phi(x) s^T - \frac{1}{\eta} \eta \phi(x) s^T) - K |s| - s^T \varepsilon \\ &= -K |s| - s^T \varepsilon \end{aligned} \tag{21}$$

Selecting

$$\|K\| > \max(\varepsilon) \tag{22}$$

Then it satisfies Lyapunov condition $\dot{V} < 0$.

5. SIMULATION STUDIES

5.1 Simulation setup

Three-link rotary robot manipulator is shown in Fig. 2. The robot has a mass of each link as $m_1 = 8\text{kg}$, $m_2 = 1.5\text{kg}$, $m_3 = 1\text{kg}$, and each link length is $L_1 = 0.07\text{m}$, $L_2 = 0.48\text{m}$, $L_3 = 0.425\text{m}$. The each joint of the robot is required to follow the sinusoidal trajectory.

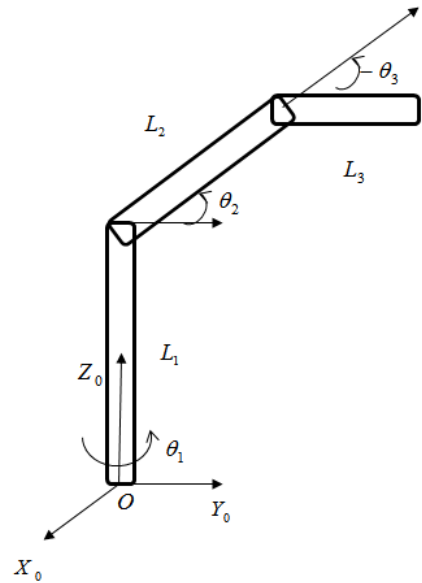
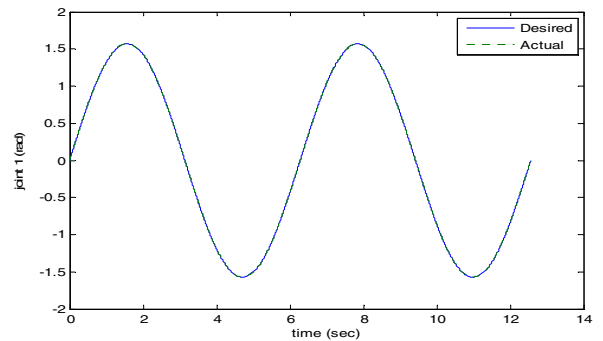


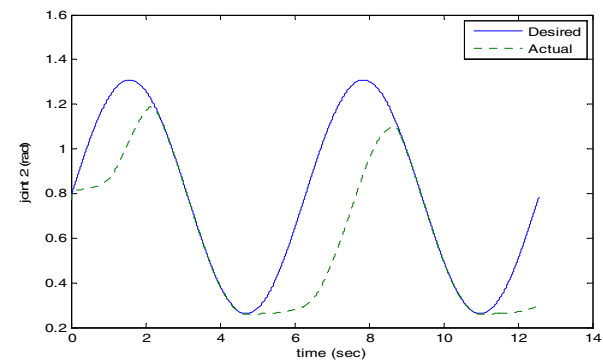
Fig. 2 Three link rotary robot

5.2 Sliding mode control scheme

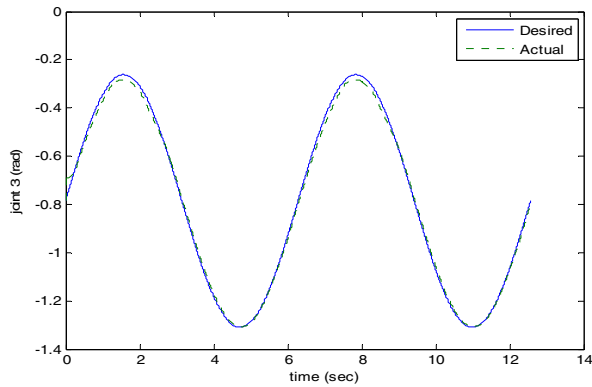
The controller gains are $\lambda = 10$ and $K = \operatorname{diag}[10,10,10]$. The robot is required to follow the sinusoidal trajectory for each joint. We see that the tracking error of joint 2 is notable.



(a) Joint 1

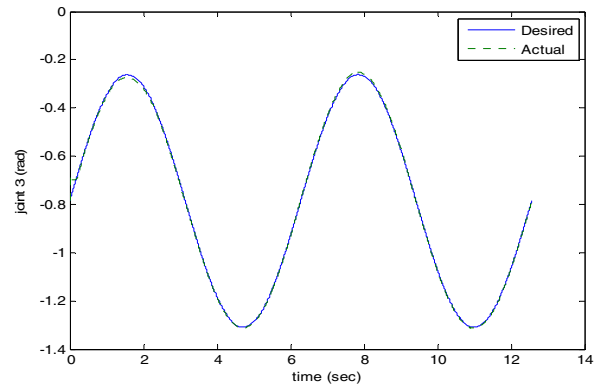


(b) Joint 2



(c) Joint 3

Fig. 3. Joint control performances by the sliding mode control scheme



(c) Joint 3

Fig. 4. Joint control performances by the neuro-sliding mode control scheme

5.3 Neuro-sliding mode control scheme

The same task has been conducted with neuro-sliding mode control method. The neural network structure is 6-9-3 for input, hidden, and output layer, respectively. The learning rate has been optimized as $\eta = 0.0017$. We see that the error of joint 2 has been reduced remarkably.

Fig. 5 shows the corresponding neural network output signals that compensate for uncertainties. We see that the compensation signal for joint2 is relatively large.

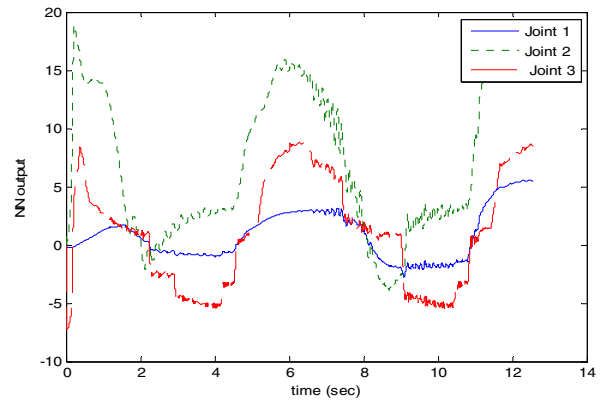
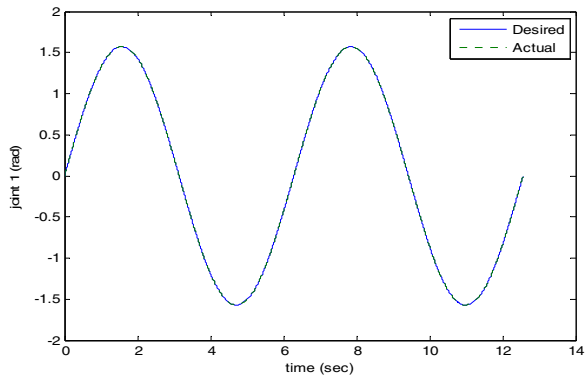
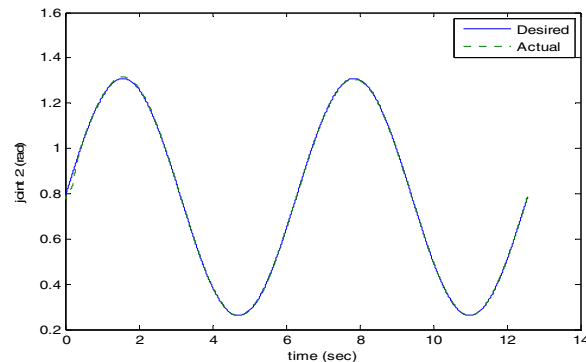


Fig. 5. Neural network outputs



(a) Joint 1



(b) Joint 2

6. CONCLUSION

A non model-based sliding mode control scheme has been combined with neural network to estimate robot dynamic model. A neuro-sliding mode control method has been introduced. Stability has been analyzed for robot manipulators. Simulation studies of joint tracking control performance for a three link rotary robot have been conducted. Tracking performances by the neuro-sliding mode control turned out to be better.

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REFERENCES

- [1] Z. Qu and D. Dawson, "Robust tracking control of robot manipulators", *IEEE Press*, 1996,
- [2] L. Sciavicco and B. Siciliano, "Modeling and control of robot manipulators", *McGraw-Hill Company*, 1996

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- [3] F. L. Lewis, S. Jagannathan, and A. Yesildirek, "Neural network control of robot manipulators and nonlinear systems", *Taylor & Francis*, 1999.
 - [4] S. Jung and T. C. Hsia, "Neural network Inverse Control Techniques for PD Controlled Robot Manipulator", *Robotica*, vol. 19, no. 3, pp. 305-314, 2000.
 - [5] S. S. Ge and C. Wang, "Direct adaptive NN control of a class of nonlinear systems," *IEEE Trans. on Neural Networks*, vol. 13, no. 1, pp. 214-221, 2002.
 - [6] H. Hashimoto, "A microprocessor-based robot manipulator control with sliding mode", *IEEE Trans. on Industrial Electronics*, vol. 34, no. 1, pp. 11-18, 1987.
 - [7] Y. Istefanopulos, E. M. Jafarov, and M. N. A. Parlakci, "A new robust continuous sliding mode control for robot manipulators with parameter perturbation", *American Control Conference*, pp. 3202-3205, 2002.
 - [8] M. Soltanpour, P. Otadolajam, M. H. Khoban, "Robust control strategy for electrically driven robot manipulators: adaptive fuzzy sliding mode", *IET Science, Measurement, & Technology*, pp. 322-334, 2015.
 - [9] D. E. Chaouch, Z. Ahmed-Foithi, and M. F. Khelfi, "A sliding mode based control of 2dof robot manipulator using neural network", *International conference on Sciences of Electronics Technologies of Information and Telecommunications*, pp. 906-911, 2012.
 - [10] Z. Chen, J. Zhang, Z. Wang, J. Zeng, "Sliding mode control of robot manipulators based on neural network reaching law", *IEEE Conference on Control and Automation*, pp. 370-373, 2007.
 - [11] M. Salen and M. F. Khelfi, "Online RBF and fuzzy based sliding mode control of robot manipulator", *International conference on Sciences of Electronics Technologies of Information and Telecommunications*, pp. 896-901, 2012.