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Adaptive RBFNN based Fuzzy Sliding Mode Control for Underwater Two Joints Manipulator in Condenser

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Abstract: Adaptive Radial basis function neural network (RBFNN) based fuzzy sliding mode controller for underwater two joints manipulator in condenser is proposed. The RBFNN is used to approximate the manipulator system dynamics, the weights of the RBFNN are changed according to adaptive algorithm to hit the sliding surface and slide along it. In order to guarantee the stability and the convergence of the system, the sliding mode control gain is adjusted by adaptive fuzzy system to compensate the network approximation error and the external disturbances. The simulation results demonstrate that the proposed control scheme is feasible and effective.

Key words: Underwater two joints manipulator, condenser, sliding mode control, RBFNN, adaptive fuzzy system

INTRODUCTION

Condenser is one kind of larger heat exchanger in power plant, underwater two joints manipulator is used to clean fouling in condensing tubes and improves the thermal efficiency of condenser, trajectory tracking is a key problem for underwater manipulator, because manipulator is a complicated controlled object with highly nonlinear,strong coupling and uncertainty such as friction,variable load which make precise trajectory tracking difficult to achieve. To design a controller for manipulator, it is necessary to have the exact trajectory tracking performance for reference inputs and the robustness for the external disturbances. Many kinds of control schemes have been proposed in the field of manipulator control during the past decades, such as PID controller, adaptive controller, intelligent controller, etc, however, when these conventional feedback controllers are directly applied to nonlinear systems, they suffer from poor performance and low robustness.

Sliding Mode Control (SMC) is an effective approach for trajectory tracking control of multi-joint robots (Ak and Cansever, 2008; Amrane and Sidoroff, 2011; Lee and Choi, 2004; Moosavian *et al*., 2007), the advantage of SMC is its invariance against parametric uncertainties and external disturbances but problem still exist owing to that SMC has the non-continuous switch feature, it can cause high frequency chattering of the system which can excite non-modeled high frequency component to cause remarkable disturbance and even make the system unstable.

Merging sliding mode control with Neural Networks (NN) control appeared to be a good idea and many researchers have published various control schemes based on this idea (Nazari and Naraghi, 2008), a few main ideas seem to be prevailing, in (Liao *et al*., 2009) the adaptive Radial basis function neural network (RBFNN) based sliding mode control (ARBSMC) attempts to apply RBFNN in the estimation of the nonlinear robot function, however, the main problem is that the control gain is also estimated.

Based on (Sankaranarayanan and Mahindrakar, 2009; Wang and Su, 2007), this study combined neural networks, fuzzy control and sliding mode control to design an Adaptive RBFNN Based Fuzzy Sliding Mode Controller (ARBFSMC) for underwater two joints manipulator. The RBFNN is used to estimate the model of system dynamic, the weights of the RBFNN are changed according to adaptive algorithm to hit the sliding surface and slide along it, in order to guarantee the stability and the convergence of the system, the sliding mode control gain is adjusted by adaptive fuzzy system to compensate the network approximation error and the external disturbances.

MODEL OF UNDERWATER TWO JOINTS MANIPULATOR

The dynamic model of underwater two joints manipulator is expressed in the following Lagrange form:

$$M(q)\ddot{q}+C(q,\dot{q})\dot{q}+G(q)+F(\dot{q})+d = T \tag{1}$$

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where, $q, \dot{q}, \ddot{q} \in R^n$ are the joint position, velocity and acceleration vectors, respectively, $M(q) \in R^{n \times n}$ denotes the inertia matrix, $C(q, \dot{q}) \in R^{n \times n}$ expresses centrifugal torques, $G(q) \in R^n$ is the gravity vector, $F(\dot{q}) \in R^n$ is the friction, $d \in R^n$ is the external disturbances, $T \in R^{n+1}$ is the control input.

The model 1 is characterized by the following structural properties which are of importance to our stability analysis.

- **Property 1:** M(q) is a positive definite symmetric matrix for all q
- **Property 2:** M(q)-2C(q, q) is a skew symmetric matrix that is:

$$\xi^T (M(q)-2C(q,\dot{q}))\xi = 0 \tag{2}$$

where, ξ is a $n \times 1$ nonzero vector.

SLIDING MODE CONTROLLER

The control objective is to drive the joint position q to the desired position q_d. The tracking error, velocity error, $\dot{q}_r$ and $\ddot{q}_r$ are also defined as:

$$e = q_d-q,\ \dot{e} = \dot{q}_d-\dot{q},\ \dot{q}_r = \dot{q}_d+?e,\ \ddot{q}_r = \ddot{q}_d+\lambda\dot{e} \tag{3}$$

The sliding surface is:

$$s = \dot{e}+\lambda e \tag{4}$$

where, $\lambda = \text{diag}(\lambda_1, \lambda_2,..., \lambda_n)$, $(\lambda_i>0)$ is a positive constant.

From Eq. 3-4 and 1 can be written as follows:

$$M\dot{s} = M\ddot{q}_r+C\dot{q}_r+G+F+d-Cs-T = -Cs-T+f+d \tag{5}$$

where, the nonlinear robot function is:

$$f = M\ddot{q}_r+C\dot{q}_r+G+F \tag{6}$$

The control input can be designed as:

$$T=\hat{M}\ddot{q}_r+\hat{C}\dot{q}_r+\hat{G}+As+K\text{sgn}(s) \tag{7}$$

where, $\hat{M}, \hat{C}, \hat{G}$ are the estimations of M, C, G, respectively, $K = [K_{11}, K_{ii},..., K_{nn}]$ is a diagonal positive definite matrix and $A = \text{diag}[a_1, a_i,\dots, a_n]$ is also a diagonal positive definite matrix, when the parameters are chosen appropriately, the tracking error could be closed to zero

Adaptive RBFNN controller: Because the accurate of system model is often difficult to obtain, a RBF neural network is used to approximate the nonlinear function f of the underwater manipulator:

$$\hat{f} = \hat{\omega}^T\phi(x) \tag{8}$$

where, $\hat{f}$ and $\hat{\omega}^T$ are estimate of f and the weight vector of the RBF neural network ω^T, the vector $\phi(x)$ is Gaussian type of functions defined element-wise as:

$$\phi_i(x) = \exp\left(-\frac{\|x-c_i\|}{b_i^2}\right) \tag{9}$$

where, c_i is the central position of neuron i, b_i is the spread factor of the Gaussian function, $x = [e\ \dot{e}\ q_d\ \dot{q}_d\ \ddot{q}_d]^T$ is input signal of neural network, the approximated system model can be described as:

$$f = \omega^{*T}\phi(x)+\varepsilon \tag{10}$$

in Eq. 10, approximation error vector is ε and ω^* is the optimal weight vector of the RBF neural network, weight vector $\hat{\omega}$ of the RBF network $\hat{\omega}^T\phi(x)$ is updated by the following adaptive mechanism:

$$\dot{\hat{\omega}} = \Gamma\phi(x)s^T \tag{11}$$

define the control input T as:

$$T = \hat{f}+(e_N+b_d)\text{sgn}(s)+As \tag{12}$$

$(\varepsilon_N+b_d)\text{sgn}(s)$ is chosen as an auxiliary controller to compensate network approximation error and external disturbances, $\|\varepsilon\| \le \varepsilon_N$, $\|d\| \le b_d$.

Putting Eq. 10 into 5 leads to:

$$\begin{aligned} M\dot{s} &= -Cs+d+\omega^{*T}\phi(x)+e-\hat{\omega}^T\phi(x)-K\text{sgn}(s)-As \\ &= -Cs+\tilde{\omega}\phi(x)-(e_N+b_d)\text{sgn}(s)-As+(e+d) \end{aligned} \tag{13}$$

STABILITY ANALYSIS

Defining a Lyapunov function:

$$V = \frac{1}{2}s^TMs+\frac{1}{2}\tilde{\omega}^T\mu^{-1}\tilde{\omega} \tag{14}$$

differentiating V with respect to time, we have:

$$\begin{aligned} \dot{V} &= \frac{1}{2}s^T\dot{M}s+s^TM\dot{s}-\tilde{\omega}^T\mu^{-1}\dot{\hat{\omega}} \\ &= \frac{1}{2}s^T(\dot{M}-2C)s+s^T(M\dot{s}+Cs)-\tilde{\omega}^T\mu^{-1}\dot{\hat{\omega}} \\ &= s^T\left[\tilde{\omega}^T\phi(x)-(e_N+b_d)\text{sgn}(s)+e+d\right]-\tilde{\omega}^T\mu^{-1}\dot{\hat{\omega}} \\ &= s^T\left[-(e_N+b_d)\text{sgn}(s)-As+\tau\right] \\ &= -s^TAs-\|s\|(e_N+b_d)+s^T\tau \\ &\le 0 \end{aligned} \tag{15}$$

Where:

$$\tilde{\omega} = \omega^{*}-\hat{\omega} \quad (16)$$

$$\tau = \varepsilon+d \quad (17)$$

Eq. 11 with 14 is the reaching condition for the sliding variable vector S to reach the sliding mode (s = 0) in a finite time.

ADAPTIVE FUZZY GAIN CONTROL

Actually, the external disturbances are unknown, although the system is stable, for instance, the impact of underwater is variable at different times and locations and the chattering on the sliding surface is caused by the constant value of ε_N, b_d and the discontinuous function sgn(S), the corrective control gain ε_N, b_d may choose larger number which causes the chattering on the sliding surface, or choose smaller number which cause increasing of reaching time and tracking error, using fuzzy controller to adjust the corrective control gain in sliding mode control, system performance can be improved.

Let the control gain $(\varepsilon_N+b_d)\mathrm{sgn}(s)$ be replaced by a fuzzy gain k, the new control input is then written as:

$$T = \hat{f}+k+As \quad (18)$$

where, $k = [k_1,..., k,...,, k_n]^T$ is estimated by an individual fuzzy system, the rule base of the fuzzy system can be decided as follows:

$$\begin{array}{l} \text{IF } s_i \text{ is NB, THEN } k_i \text{ is NB} \\ \text{IF } s_i \text{ is NM, THEN } k_i \text{ is NM} \\ \text{IF } s_i \text{ is NS, THEN } k_i \text{ is NS} \\ \text{IF } s_i \text{ is ZE, THEN } k_i \text{ is ZE} \\ \text{IF } s_i \text{ is PS, THEN } k_i \text{ is PS} \\ \text{IF } s_i \text{ is PM, THEN } k_i \text{ is PM} \\ \text{IF } s_i \text{ is PB, THEN } k_i \text{ is PB} \end{array} \quad (19)$$

where, NB, NM, NS, PS, PM, PB are seven fuzzy sets, N stands for negative, P positive, B big, M medium, S small, Z zero, they are all Gaussian membership functions defined as follows:

$$\mu_A(x_i) = \exp\left[-\left(\frac{x-\alpha}{\sigma}\right)^2\right] \quad (20)$$

k_i can be written as:

$$k_i(x_i) = \frac{\sum_{m=1}^{M} \theta_{k_i}^{m} \mu_{A^m}(s_i)}{\sum_{m=1}^{M} \mu_{A^m}(s_i)} = \theta_{k_i}^{T} \Psi_{k_i}(s_i) \quad (21)$$

where $\theta_{k_i} = [\theta_{k_i}^{1},...,\theta_{k_i}^{m},...,\theta_{k_i}^{M}]^T$ is the vector of the center of the membership functions of k_i, $\Psi_{k_i}(s_i) = [\psi_{k_i}^{1}(s_i),..., \psi_{k_i}^{m}(s_i),...,\psi_{k_i}^{M}(s_i)]^T$ is the vector of the height of the membership functions of k_i in which:

$$\psi^m(x) = \frac{\prod_{i=1}^{n} \mu_{A^m}(x_i^*)}{\sum_{m=1}^{M}\prod_{i=1}^{n} \mu_{A^m}(x_i^*)}$$

and M is the amount of the rules.

Define θ_{k_id}, so that $k_i = \theta_{k_id}^{T}\Psi_{k_i}(s_i)$ is the optimal compensation for τ, according to Wang's theorem, there exists ω_i>0 satisfying:

$$\left|\tau_i - \theta_{k_id}^{T}\Psi_{k_i}(s_i)\right| \le \omega_i \quad (22)$$

where, ω_i can be as small as possible, define:

$$\tilde{\theta}_{k_i} = \theta_{k_i} - \theta_{k_id} \quad (23)$$

then:

$$k_i = \tilde{\theta}_{k_i}^{T}\Psi_{k_i}(s_i) + \theta_{k_id}^{T}\Psi_{k_i}(s_i) \quad (24)$$

a Lyapunov function candidate is chosen as:

$$V=\frac{1}{2}s^TMs+\frac{1}{2}\tilde{\omega}^T\mu^{-1}\tilde{\omega}+\frac{1}{2}\sum_{i=1}^{n}(\tilde{\theta}_{k_i}^{T}\tilde{\theta}_{k_i}) \quad (25)$$

consider the derivative of V:

$$\begin{aligned} \dot{V} &= -s^TAs+s^T(\tau-k)+\sum_{i=1}^{n}(\tilde{\theta}_{k_i}^{T}\dot{\tilde{\theta}}_{k_i}) \\ &= -s^TAs+\sum_{i=1}^{n}s_i(\tau_i-k_i)+\sum_{i=1}^{n}(\tilde{\theta}_{k_i}^{T}\dot{\tilde{\theta}}_{k_i}) \\ &= -s^TAs+\sum_{i=1}^{n}s_i\left(\tau_i-(\tilde{\theta}_{k_i}^{T}\Psi_{k_i}(s_i)+\theta_{k_id}^{T}\Psi_{k_i}(s_i))\right)+\sum_{i=1}^{n}(\tilde{\theta}_{k_i}^{T}\dot{\tilde{\theta}}_{k_i}) \\ &= -s^TAs+\sum_{i=1}^{n}s_i\left(\tau_i-\theta_{k_id}^{T}\Psi_{k_i}(s_i)\right)+\sum_{i=1}^{n}(-s_i\tilde{\theta}_{k_i}^{T}\Psi_{k_i}(s_i)+\tilde{\theta}_{k_i}^{T}\dot{\tilde{\theta}}_{k_i}) \\ &= -s^TAs+\sum_{i=1}^{n}s_i\left(\tau_i-\theta_{k_id}^{T}\Psi_{k_i}(s_i)\right)+\sum_{i=1}^{n}\tilde{\theta}_{k_i}^{T}(-s_i\Psi_{k_i}(s_i)+\dot{\tilde{\theta}}_{k_i}) \\ &= -s^TAs+\sum_{i=1}^{n}s_i\left(\tau_i-\theta_{k_id}^{T}\Psi_{k_i}(s_i)\right) \end{aligned} \quad (26)$$

Where:

$$\dot{\tilde{\theta}}_{k_i} = s_i\Psi_{k_i}(s_i) \quad (27)$$

Assume:

$$\left|\tau_i - \theta_{k_id}^{T}\Psi_{k_i}(s_i)\right| \le \omega_i \le \gamma_i\left|s_i\right| \quad (28)$$

where $0 \le \gamma_t \le 1$, then:

$$s_i\left(\tau_i - \theta_{k_{id}}^T \Psi_{k_i}(s_i)\right) \le \gamma_i |s_i|^2 = \gamma_i s_i^2 \qquad (29)$$

putting Eq. 29 into 26, we have:

$$\dot{V} \le -s^T As + \sum_{i=1}^{n} \gamma_i s_i^2 = \sum_{i=1}^{n}(-a_i s_i^2 + \gamma_i s_i^2) = \sum_{i=1}^{n}(\gamma_i - a_i) s_i^2 \le 0 \qquad (30)$$

where, $\gamma = \text{diag}[\gamma_1,..., \gamma_t,..., \gamma_n]$, $a_t > \gamma_t$, V = 0 only when s = 0.

SIMULATION

In order to verify the control method, the simulations for two link robot manipulator are conducted.

The dynamic model is presented as follow:

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + F(\dot{q}) + d = T$$

Where:

$$M(q) = \begin{bmatrix} 3.66+1.74\cos(q_2) & 0.76+0.87\cos(q_2) \\ 0.76+0.87\cos(q_2) & 0.76 \end{bmatrix}$$

$$C(q,\dot{q}) = \begin{bmatrix} -0.87\dot{q}_2 \sin(q_2) & -0.87(\dot{q}_1+\dot{q}_2)\sin(q_2) \\ 0.87\dot{q}_1 \sin(q_2) & 0 \end{bmatrix}$$

$$G = \begin{bmatrix} 3.04g\cos q_1 + 0.87g\cos(q_1+q_2) \\ 0.87g\cos(q_1+q_2) \end{bmatrix}$$

$$g = 9.8,\ d = [0.2\cos(\pi t)\ 0.2\sin(\pi t)],\ F(\dot{q}) = 0.02\text{sgn}(\dot{q})$$

the desired trajectories for two-link to be tracked are $q_{1d} = \cos(\pi t)$, $q_{2d} = \sin(\pi t)$, the initial input trajectories are defined as $[q_1\ q_2\ \dot{q}_1\ \dot{q}_2] = [0.09\ 0\ -0.09\ 0]$ for joints 1 and 2, control parameters for the sliding mode are K = diag(50, 50), Γ = diag(15, 15), A = diag(20, 20):

$$C = \begin{bmatrix} 5 & 0 \\ 0 & 5 \end{bmatrix}$$

central positions of the Gaussian function c_i are selected from -1.5 to 1.5, spread factors b_i are 0.2, initial weights of network are adjusted to zero, $\varepsilon_N = 0.2$, $b_d = 0.1$. α is chosen as $-\pi/3$, $-\pi/6$, $-\pi/12$, 0, $\pi/12$, $\pi/6$, $\pi/3$. σ is $\pi/24$. The simulation result is shown in Fig 1-3.

Figure 1-3 are position tracking for joint 1 and 2 using the SMC, ARBSMC and ARBFSMC, respectively. The blue lines in Fig. 1-3 are desired trajectories of two joints of underwater manipulator, the red ones are the response curves.

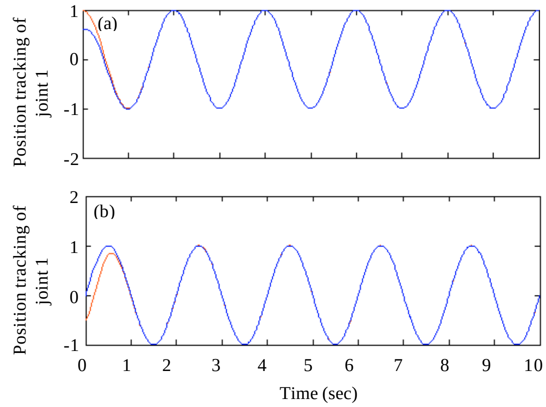

Fig. 1: Position tracking for joint 1 and 2 by using SMC

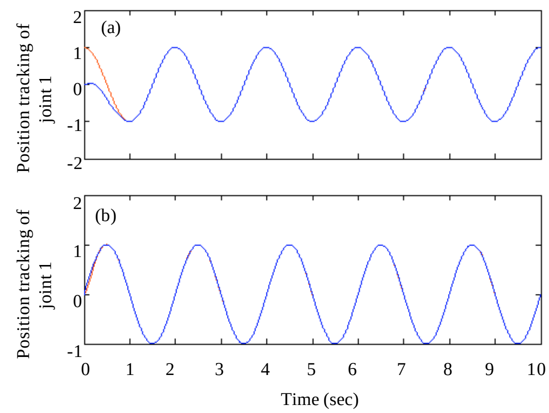

Fig. 2: Position tracking for joint 1 and 2 by using ARBSMC

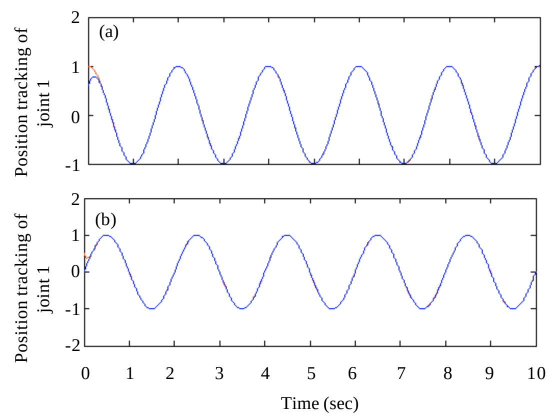

Fig. 3: Position tracking for joint 1 and joint2 by using ARBFSMC

The three control schemes all can track approximately the desired trajectory. Figure 1 and 2 demonstrate that the

SMC and the ARBSMC seem to be able to drive the manipulator to its desired positions, but if the control gain is estimated largely, it can cause high frequency chattering of the system, the chattering increases controller burden and easily damages controller parts. In Fig. 3, it can be seen that the tracking converge to the desired trajectories more quickly. From the comparison of Figs.1-Fig.3, it is concluded that the ARBFSMC proposed in this study performs best.

CONCLUSION

In this study, adaptive sliding mode control based on RBFNN and fuzzy logic is proposed for underwater two joints manipulator. The control scheme is designed for the purpose of effectively eliminating the system uncertainty and guaranteeing system stability without a prior knowledge of the system uncertainty. The simulation results demonstrate that the control scheme is feasible and effective.

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REFERENCES

Ak, A.G. and G. Cansever, 2008. Fuzzy sliding mode controller with neural network for robot manipulators control. Proceedigns of the 10th International Conference on Automation, Robotics and Vision, December 17-20, 2008, Hanoi, pp: 1556-1561.

Amrane, M.N. and F. Sidoroff, 2011. Residual modal energy evaluating of fatigue damaged composite structure. Mechanics, 17: 45-49.

Lee, M.J. and Y.K. Choi, 2004. An adaptive neurocontroller using RBFN for robot manipulators. IEEE Trans. Ind. Electron., 51: 711-717.

Liao, Q., C. Wang and Y. Mei, 2009. Sliding mode control for Multi-robot formation. Proceedings of the IEEE Conference on Robotics, Automation and Mechatronics, September 21-24, 2009, Chengdu, pp: 395-398.

Moosavian, S.A.A., A. Takhmar and M. Alghooneh, 2007. Regulated sliding mode control of a biped robot. Proceedings of the International Conference on Mechatronics and Automation, August 5-8, 2007, Harbin, pp: 1547-1552.

Nazari, V. and M. Naraghi, 2008. Sliding mode fuzzy control of a skid steer mobile robot for path following control. Proceedings of the 10th International Conference on Automation, Robotics and Vision, December 17-20, 2008, Hanoi, pp: 549-554.

Sankaranarayanan, V. and A.D. Mahindrakar, 2009. Control of a class of underactuated mechanical systems using sliding modes. IEEE Trans. Robotics, 25: 459-467.

Wang, X. and X. Su, 2007. Modeling and sliding mode control of the upper arm of a shotcrete robot with hydraulic actuator. IEEE International Conference on Integration Technology, March 20-24, 2007, Shenzhen, pp: 714-718.