Research Article

Composite Learning Sliding Mode Control of Flexible-Link Manipulator

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This paper studies the control of a flexible-link manipulator with uncertainty. The fast and slow dynamics are derived based on the singular perturbation (SP) theory. The sliding mode control is proposed while the adaptive design is developed using neural networks (NNs) and disturbance observer (DOB) where the novel update laws for NN and DOB are designed. The closed-loop system stability is guaranteed via Lyapunov analysis. The effectiveness of the proposed method is verified via simulation test.

1. Introduction

Flexible manipulators own the good characteristics of light weight, fast motion, and low energy consumption. Thus flexible manipulators can be used in many applications [1]. Due to the flexibility, the response of the manipulator shows oscillation while it is difficult to obtain high tracking precision. These are the two major challenges within the control of flexible manipulator [2]. As a result, many works have been aimed at controlling flexible manipulator [3–7].

In the literature, to deal with the dynamics transformation, output redefinition and SP method can be used. In [3], to avoid the difficulty of nonminimum phase system, the output is redefined for system transformation. In [8, 9], the observer based design is presented when the states are not available. In [10, 11], NNs are constructed to approximate the whole system uncertainty. The singularly perturbed model [12] is proposed to obtain fast dynamics and slow dynamics. Some other works can be found in [13, 14].

As discussed in [1], to achieve high tracking accuracy, based on output redefinition or SP method, efficient learning of system uncertainty and disturbance should be key factor. For system uncertainty, fuzzy logic system (FLS)/NNs can be employed. In the literature, there exist many results of intelligent control which employ intelligent system for approximation and then construct the controller [15–21]. One

concern is whether the FLS or NN has successfully fulfilled the task of approximation. To verify the effectiveness, the approximation error should be checked. However, usually it is not possible to derive the signal directly. In [1], with the output redefinition, the composite learning [22] is proposed with the serial-parallel estimation model. It is shown that the obtained predictor error can highly enhance the update of the learning system.

While the uncertainty commonly exists, disturbance might deteriorate the system tracking performance. With the upper bound for robust design, sliding mode control is studied. However, in this way, it brings energy consumption. One concern is to develop the efficient learning to follow the trend of the disturbance. The basic idea is that if the disturbance observer is fast enough compared with the system dynamics then to a great certain it can follow the trend of the disturbance. Some results can be referred to in [23, 24]. In [25], the attempt using composite learning with NN and DOB is developed for a flexible-link manipulator.

It is noted that in [25], the design is using backstepping scheme. To facilitate the design procedure, borrowing the idea of composite learning, the composite sliding mode control of n degrees of freedom flexible-link manipulators will be proposed.

The rest of the paper is arranged as follows. Section 2 presents the flexible-link manipulator dynamics and the

transformation with SP approach. The control of the slow subsystem and the fast subsystem is given in Sections 3 and 4, respectively. The simulation is shown in Section 5 while the conclusion is discussed in Section 6.

2. Dynamics Model

The model of n degrees of freedom flexible-link manipulators is as follows:

$$M \begin{bmatrix} \ddot{\theta} \\ \ddot{\delta} \end{bmatrix} + \begin{bmatrix} S_1(\theta, \delta, \dot{\theta}, \dot{\delta}) \\ S_2(\theta, \delta, \dot{\theta}, \dot{\delta}) \end{bmatrix} + \begin{bmatrix} D_1 & 0 \\ 0 & D_2 \end{bmatrix} \begin{bmatrix} \dot{\theta} \\ \dot{\delta} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & K_2 \end{bmatrix} \begin{bmatrix} \theta \\ \delta \end{bmatrix} = \begin{bmatrix} u \\ 0 \end{bmatrix} + \begin{bmatrix} f_d \\ 0 \end{bmatrix}, \quad (1)$$

where the physical meanings of M , $S_1(\theta, \delta, \dot{\theta}, \dot{\delta})$, $S_2(\theta, \delta, \dot{\theta}, \dot{\delta})$, D_1 , D_2 , K_2 , u , and f_d can be found in [25].

With modal order as m , the vectors $\theta \in R^{n \times 1}$ and $\delta \in R^{nm \times 1}$ are defined as $\theta = [\theta_1, \dots, \theta_n]^T$ and $\delta = [\delta_{1,1}, \dots, \delta_{1,m}, \dots, \delta_{n,1}, \dots, \delta_{n,m}]^T$, where θ_i denotes the i -th joint angle variable and $\delta_{i,j}$ is the i -th link j -th modal variable.

Let $M^{-1} = \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}$ and denote $S_1(\theta, \delta, \dot{\theta}, \dot{\delta})$ and $S_2(\theta, \delta, \dot{\theta}, \dot{\delta})$ as S_1 and S_2 . Then the dynamics can be written as

$$\begin{aligned} \ddot{\theta} &= -H_{11}(S_1 + D_1\dot{\theta} - u - f_d) \\ &\quad - H_{12}(S_2 + D_2\dot{\delta} + K_2\delta) \\ \ddot{\delta} &= -H_{21}(S_1 + D_1\dot{\theta} - u - f_d) \\ &\quad - H_{22}(S_2 + D_2\dot{\delta} + K_2\delta). \end{aligned} \quad (2)$$

Define control input

$$u = u_s + u_f, \quad (3)$$

where u_s and u_f are the control inputs of the slow subsystem and the fast subsystem, respectively.

Supposing $k = \min K_2$, define $\rho = 1/k$, $\rho\phi = \delta$, and $\beta = \rho K_2$. The slow subsystem can be obtained as

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= \zeta + bu_s + bf_{ds} = \zeta + b_0u_s + d, \end{aligned} \quad (4)$$

where $x_1 = \theta$, $x_2 = \dot{\theta}$, $b = H_{11s} - H_{12s}H_{22s}^{-1}H_{21s}$, $\Delta b = b - b_0$, $\zeta = b(-S_{1s} - D_{1s}\dot{\theta}_s)$, and $d = bf_{ds} + \Delta bu_s$.

Remark 1 (b_0 is the nominal value of b). Define $\psi_1 = \phi - \phi_s$, $\psi_2 = \sqrt{\rho}\dot{\phi}$, and $\varsigma = t/\sqrt{\rho}$. The fast dynamics are written as

$$\begin{aligned} \frac{d\psi_1}{d\varsigma} &= \psi_2 \\ \frac{d\psi_2}{d\varsigma} &= -H_{22s}\beta\psi_1 - H_{22s}D_{2s}\sqrt{\rho}\psi_2 + H_{21s}u_f \end{aligned} \quad (5)$$

and the following expression is obtained:

$$\frac{d\psi}{d\varsigma} = P_f\psi + Q_fu_f, \quad (6)$$

where $\psi = [\psi_1, \psi_2]^T$, $P_f = \begin{bmatrix} 0 & I \\ -H_{22s}\beta & -H_{22s}D_{2s}\sqrt{\rho} \end{bmatrix}$, and $Q_f = [0, H_{21s}]^T$.

Remark 2. With the SP method in [12, 26], the fast dynamics (5) and the slow dynamics (4) are obtained. The detail to obtain (4) and (6) can be found in [25].

3. Composite Learning Sliding Mode Control of Slow Subsystem

Backstepping design is employed for controller design in [25] and during the analysis it will introduce the error signal in each step. In this paper, the sliding mode control will be proposed with composite learning design.

Define $e_1 = x_1 - x_{1d}$ and $e_2 = x_2 - \dot{x}_{1d}$, where x_{1d} and $\dot{x}_{1d}$ are the desired joint angle trajectories.

Define the sliding surface

$$e_s = e_2 + ce_1, \quad (7)$$

where c is positive matrix.

Define $J = L_F\zeta$ and $x = [x_1^T, x_2^T]^T$, where L_F is a positive design constant. The following approximation exists:

$$\hat{J} = \widehat{\omega}^T \vartheta(x), \quad (8)$$

where $\widehat{\omega} \in R^{p \times n}$ is the weight matrix, p is the number of hidden nodes, and ϑ is the NN basis vector.

The derivative of e_s is calculated as

$$\begin{aligned} \dot{e}_s &= \dot{e}_2 + c\dot{e}_1 = \zeta + b_0u_s + d - \ddot{x}_{1d} + c\dot{e}_1 \\ &= L_F^{-1}\widehat{\omega}^T \vartheta(x) + b_0u_s + L_F^{-1}\varepsilon + d - \ddot{x}_{1d} + c\dot{e}_1 \\ &= L_F^{-1}\widehat{\omega}^T \vartheta(x) + b_0u_s + F - \ddot{x}_{1d} + c\dot{e}_1, \end{aligned} \quad (9)$$

where $F = d + L_F^{-1}\varepsilon$ and $\widehat{\omega}$ is the optimal weights matrix of function J approximation.

Define the prediction error as

$$\begin{aligned} Z_N &= x_2 - \widehat{x}_2 \\ \dot{\eta}_2 &= L_F^{-1}\widehat{\omega}^T \vartheta(x) + b_0u_s + \widehat{F} + k_p Z_N, \end{aligned} \quad (10)$$

where $k_p > 0$ is the design constant and $\widehat{F}$ is adaptive signal constructed as

$$\begin{aligned} \widehat{F} &= L(x_2 - z) \\ \dot{z} &= L_F^{-1}\widehat{\omega}^T \vartheta(x) + b_0u_s + \widehat{F} - L^{-1}(\gamma_z Z_N + e_s) \end{aligned} \quad (11)$$

with $L > 0$ and $\gamma_z > 0$ as design parameters.

Define $\widetilde{\omega} = \widehat{\omega} - \omega$, $\widetilde{F} = F - \widehat{F}$ where $\widehat{\omega}$ is the estimation of ω and $\widehat{F}$ is the estimation of F . Then we have

$$\dot{\widetilde{F}} = L(\dot{x}_2 - \dot{z}) = L[L_F^{-1}\widehat{\omega}^T \vartheta(x) + \widetilde{F}] + \gamma_z Z_N + e_s. \quad (12)$$

Finally u_s is proposed as

$$u_s = b_0^{-1} \left[-L_F^{-1} \tilde{\omega}^T \vartheta(x) - k_1 e_s - k_2 \text{sign}(e_s) - \tilde{f} + \ddot{x}_{1d} - c\dot{e}_1 \right] \quad (13)$$

where $k_1 \in R^{n \times n}$ and $k_2 \in R^{n \times n}$ are positive definite symmetric matrices.

The NN update law is proposed as

$$\dot{\hat{\omega}} = \gamma \left[\vartheta(x) L_F^{-1} (e_s + \gamma_z Z_N)^T - \sigma \hat{\omega} \right], \quad (14)$$

where $\gamma > 0$ and $\sigma > 0$ are design constants.

The error dynamics are obtained as

$$\dot{e}_s = L_F^{-1} \tilde{\omega}^T \vartheta - k_1 e_s - k_2 \text{sign}(e_s) + \tilde{f} \quad (15)$$

$$\dot{\tilde{f}} = \dot{f} - L \left[L_F^{-1} \tilde{\omega}^T \vartheta(x) + \tilde{f} \right] - \gamma_z Z_N - e_s \quad (16)$$

$$\dot{\tilde{\omega}} = -\gamma \left[\vartheta(x) L_F^{-1} (e_s + \gamma_z Z_N)^T - \sigma \hat{\omega} \right] \quad (17)$$

and the derivative of Z_N is obtained as

$$\dot{Z}_N = L_F^{-1} \tilde{\omega}^T \vartheta + \tilde{f} - k_p Z_N. \quad (18)$$

Theorem 3. *With the controller (13), NN update law (14), and nonlinear DOB design (11), then all the signals in (A.1) are bounded.*

See appendix for proof.

4. Sliding Mode Control of Fast Subsystem

The control input u_f of the fast subsystem is designed as [25]

$$u_f = -(GQ_f)^+ \left[GP_f \psi + K_f \text{sat}(\xi) \right], \quad (19)$$

where K_f is the positive definite gain matrix.

The control input is presented as

$$u = u_s + u_f = b_0^{-1} \left[-L_F^{-1} \tilde{\omega}^T \vartheta(x) - k_1 e_s - k_2 \text{sat}(e_s) - \tilde{f} + \ddot{x}_{1d} - c\dot{e}_1 \right] - (GQ_f)^+ \left[GP_f \psi + K_f \text{sat}(\xi) \right]. \quad (20)$$

5. Simulation Example

To verify the effectiveness of the proposed method, simulation of the 2-DOF flexible-link manipulators is given. The parameter selection is selected as the same as [25]. The reference signals are given as

$$\begin{aligned} x_{1d}(1) &= \sin(0.3\pi t) \\ x_{1d}(2) &= -\cos(0.3\pi t). \end{aligned} \quad (21)$$

The approach in this paper is marked as “CL-SMC” which means composite learning sliding mode control while the design using tracking error to update NN is denoted as “NN-SMC.”

The control parameters are set as $k_1 = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}$, $k_2 = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix}$, $k_p = 0.5$, $\gamma = 10$, $\gamma_z = 100$, $\sigma = 1$, $L = 10$, $\rho = 0.02$,

FIGURE 1: Joint angle of link 1. (a) System response. (b) Tracking error.

$K_f = 0.5I_{4 \times 4}$, $L_F = 2$, $G = [0.1I_{4 \times 4}, I_{4 \times 4}]$, $f_d(1) = 0.5 \sin t$, $f_d(2) = 0.5 \sin t$, and $c = 0.5I_{2 \times 2}$. The system tracking of link 1 and link 2 is shown in Figures 1 and 2, respectively. It is observed that under “CL-SMC,” much higher tracking accuracy can be obtained. Also the steady error is small for “CL-SMC” while for “NN-SMC” the error is large and chattering all the time. From Figures 3 and 4, the composite learning can closely follow the compound uncertainty while under “NN-SMC” the NN cannot fulfill the task. It confirms the rationales using composite learning. The responses of NN weights, control inputs, and sliding mode surface are shown in Figures 5, 6, and 7, respectively. The signal e_s is converging the small neighborhood of zero.

6. Conclusion

Considering the flexible-link manipulators, this paper proposed the sliding mode control with NN and DOB for compound estimation. The composite learning control scheme can greatly enhance the tracking performance. The simulation results confirms the design philosophy that the composite learning can efficiently fulfil the estimation task.

Appendix

Proof. The Lyapunov candidate is chosen as

$$V = V_1 + V_2 + V_3 + V_4, \quad (A.1)$$

where $V_1 = (1/2)e_s^T e_s$, $V_2 = (1/2)\tilde{f}^T \tilde{f}$, $V_3 = (1/2\gamma)\text{tr}(\tilde{\omega}^T \tilde{\omega})$, and $V_4 = (1/2)\gamma_z Z_N^T Z_N$.

FIGURE 2: Joint angle of link 2. (a) System response. (b) Tracking error.

FIGURE 3: Uncertainty estimation 1. (a) Estimation under "CL-SMC." (b) Estimation under "NN-SMC." (c) Estimation error.

FIGURE 4: Uncertainty estimation 2. (a) Estimation under "CL-SMC." (b) Estimation under "NN-SMC." (c) Estimation error.

FIGURE 5: NN response. (a) Trajectory of $\|\hat{\omega}_1\|$. (b) Trajectory of $\|\hat{\omega}_2\|$.

FIGURE 6: Control signals. (a) u_1 . (b) u_2 .

Using (15), (17), (18), and (16), the derivatives of V_i , $i = 1, \dots, 4$ can be obtained as

$$\begin{aligned}
 \dot{V}_1 &= e_s^T \dot{e}_s \\
 &= e_s^T L_F^{-1} \tilde{\omega}^T \vartheta - e_s^T k_1 e_s - e_s^T k_2 \text{sign}(e_s) + e_s^T \tilde{F} \\
 \dot{V}_2 &= \tilde{F}^T \dot{\tilde{F}} \\
 &= \tilde{F}^T \dot{\tilde{F}} - \gamma_z Z_N^T \tilde{F} - e_s^T \tilde{F} - L_F^{-1} L \tilde{F}^T \tilde{\omega}^T \vartheta - L \tilde{F}^T \tilde{F} \\
 \dot{V}_3 &= \frac{1}{\gamma} \text{tr}(\tilde{\omega}^T \dot{\tilde{\omega}}) \\
 &= -L_F^{-1} e_s^T \tilde{\omega}^T \vartheta - L_F^{-1} \gamma_z Z_N^T \tilde{\omega}^T \vartheta \\
 &\quad - \sigma \text{tr}(\tilde{\omega}^T \tilde{\omega} - \tilde{\omega}^T \omega) \\
 \dot{V}_4 &= \gamma_z Z_N^T \dot{Z}_N \\
 &= L_F^{-1} \gamma_z Z_N^T \tilde{\omega}^T \vartheta + \gamma_z Z_N^T \tilde{F} - k_p \gamma_z Z_N^T Z_N.
 \end{aligned} \tag{A.2}$$

Then the derivative of V is calculated as

$$\begin{aligned}
 \dot{V} &= -e_s^T k_1 e_s - e_s^T k_2 \text{sign}(e_s) - \sigma \text{tr}(\tilde{\omega}^T \tilde{\omega} - \tilde{\omega}^T \omega) \\
 &\quad - \gamma_z k_p Z_N^T Z_N + \tilde{F}^T \dot{\tilde{F}} - L_F^{-1} L \tilde{F}^T \tilde{\omega}^T \vartheta - L \tilde{F}^T \tilde{F}.
 \end{aligned} \tag{A.3}$$

The following inequalities exist:

$$\begin{aligned}
 \text{tr}(\tilde{\omega}^T \omega) &\leq \frac{1}{2} \text{tr}(\tilde{\omega}^T \tilde{\omega}) + \frac{1}{2} \text{tr}(\omega^T \omega) \\
 \tilde{F}^T \dot{\tilde{F}} &\leq \frac{1}{2} v_1 \tilde{F}^T \tilde{F} + \frac{1}{2 v_1} \dot{\tilde{F}}^T \dot{\tilde{F}} \\
 -\tilde{F}^T (\tilde{\omega}^T \vartheta) &\leq \frac{1}{2} v_2 \epsilon \tilde{F}^T \tilde{F} + \frac{1}{2 v_2} \text{tr}(\tilde{\omega}^T \tilde{\omega}),
 \end{aligned} \tag{A.4}$$

where $\|\vartheta\|^2 \leq \epsilon$ and v_1 and v_2 are positive scalars.

FIGURE 7: Sliding mode surface. (a) Signal $e_s(1)$. (b) Signal $e_s(2)$.

Then we have

$$\begin{aligned}
 \dot{V} &\leq -e_s^T k_1 e_s - e_s^T k_2 \text{sign}(e_s) - \gamma_z k_p Z_N^T Z_N \\
 &\quad - \frac{1}{2} \sigma \text{tr}(\tilde{\omega}^T \tilde{\omega}) + \frac{1}{2} \sigma \text{tr}(\omega^T \omega) + \frac{1}{2} v_1 \tilde{F}^T \tilde{F} \\
 &\quad + \frac{1}{2 v_1} \dot{\tilde{F}}^T \dot{\tilde{F}} + \frac{L}{2 L_F} v_2 \tilde{F}^T \tilde{F} + \frac{L}{2 v_2 L_F} \text{tr}(\tilde{\omega}^T \tilde{\omega}) \\
 &\quad - L \tilde{F}^T \tilde{F} \\
 &= -e_s^T k_1 e_s - e_s^T k_2 \text{sign}(e_s) - \gamma_z k_p Z_N^T Z_N \\
 &\quad - \left(L - \frac{1}{2} v_1 - \frac{L v_2 \epsilon}{2 L_F} \right) \tilde{F}^T \tilde{F} \\
 &\quad - \left(\frac{1}{2} \sigma - \frac{L}{2 v_2 L_F} \right) \text{tr}(\tilde{\omega}^T \tilde{\omega}) + \frac{1}{2} \sigma \text{tr}(\omega^T \omega) \\
 &\quad + \frac{1}{2 v_1} \dot{\tilde{F}}^T \dot{\tilde{F}}.
 \end{aligned} \tag{A.5}$$

By selecting appropriate parameters L , σ , and L_F to satisfy $k_d > 0$, $k_s > 0$, where

$$k_d = L - \frac{1}{2} v_1 - \frac{L v_2 \epsilon}{2 L_F} \tag{A.6}$$

$$k_s = \frac{1}{2} \sigma - \frac{L}{2 v_2 L_F},$$

it is concluded that

$$\dot{V} \leq -\chi V + \varphi, \tag{A.7}$$

where $\chi = \min[2\lambda_{\min}(k_1), 2\gamma k_s, 2k_p, 2k_d]$, $\varphi = (1/2) \sigma \text{tr}(\omega^T \omega) + (1/2 v_1) \dot{\tilde{F}}^T \dot{\tilde{F}}$.

Then

$$0 \leq V \leq \frac{\varphi}{\chi} + \left[V(0) - \frac{\varphi}{\chi} \right] e^{-\chi t}. \quad (\text{A.8})$$

It is concluded when $t \rightarrow \infty$, $V \rightarrow \varphi/\chi$ and the signals included in (A.1) are bounded. $\square$

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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