Decentralized adaptive force/position control of reconfigurable manipulator based on soft sensors

Yanli Du[1] and Quanmin Zhu[2]

Abstract

Two soft sensor control methods are proposed to deal with force/position control of reconfigurable manipulators without using wrist force sensors. Firstly, modeling uncertainties and coupling interconnection terms between the subsystems are approximated by using adaptive RBF neural network, and the soft sensor model of the contact force is established by means of adaptive RBF neural network to design hybrid force/position controller. Then, a decentralized impedance inner/force outer loop controller is designed. The reference trajectory of impedance inner controller is provided by force outer loop controller based on the fuzzy prediction, and the soft sensor model of the contact force is established by the fuzzy system. The proposed soft sensor model does not request the exact mathematical relationship between the end contact force and auxiliary variables, and provides a feasible method to replace the wrist force sensors which are expensive and easily noised by the external factors. Compared with the observer method，the proposed methods provide better position and force tracking precision.

Keywords

Reconfigurable manipulator，soft sensor，decentralized hybrid force/position control，impedance inner control，adaptive RBF neural network，fuzzy approximation

1 Introduction

Reconfigurable manipulators can form the various configurations of different degrees of freedom (DOF) to carry out tasks and are widely applied in the field of dangerous work environment, space exploration, and military, industrial, medical, entertainment etc. There are many tasks like polishing, grabbing and operation that require interaction between reconfigurable manipulator and the environment. This fact requires that the position and the contact force with the environment for reconfigurable manipulator should be controlled at the same time. So, many researchers have done lots of researches on the force and position control of the manipulator in recent years [1-10].

The force control methods of the manipulator include force/position control [1-4] and impedance control [5-10], but these methods require a wrist force sensor to be installed at the manipulator end. In the applications of industrial manipulators, high accurate and reliable force sensors are very expensive, and the use of force sensors will increase the complexity of the manipulator in electrical, mechanical and software parts. There are various uncertainties and environmental factors in the industrial field, which may have influence to the precision of the sensor and operational reliability. In recent years, to improve the reliability of the manipulator control system, external force estimation method of reconfigurable manipulator is proposed. Colomé [11] proposes a robust observer to estimate contact forces between the manipulator and the environment. The force sensor is not used in this method. In order to estimate the position and force of the manipulator during FSW processes, Qin [12] proposes a non-linear observer to estimate not only the state (position and velocity) of links, but also the external forces exerted by the robot during Friction Stir Welding (FSW) processes. In order to ensure a

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better tracking performance, the data such as real positions, velocities of links and external forces are required. Wang [13] designs an observer to approximate force，and in order to overcome the uncertainty of the environment, the adaptive law of stiffness is derived. Chan [14] proposed a force estimation method based on the active observer in the presence of the noise for the robot. It can not only estimate contact force, but also observe the state of the system. Du [15] proposes a decentralized adaptive force control method based on nonlinear joint torque observer for reconfigurable manipulator. The nonlinear observer is designed to observe the torque of each joint, and finally get the contact force by Jacobian matrix transformation.

The above methods are to estimate the contact force by the observer, which is difficult to prove the convergence of the observation error and is easily affected by the observed noise. So, in recent years, many scholars have invested in the research of force control methods based on soft sensor technology. Ren [16] and Cho [17] present a soft sensor method to solve the problem that stress signal is difficult to obtain in the health monitoring of multibody manipulator. In the method, stress signal is considered as dominant variable and angle signal is regarded as auxiliary variable. By establishing the mathematical relationship between them, a soft sensor model is proposed. Hammond [18] proposes a soft sensor method for the submillimeter contact localization and force measurement in micromanipulation. Tactile sensing experiments verify the effectiveness of the method. Yang [19] has designed a novel pneumatic soft sensor (PSS). According to the inner pressure of sensing body, PSS can measure contact force and curvature by building relation models of contact force and curvature, and its measurement accuracy is tested by a large of experiments.

The above force estimation methods based on soft sensor need to know the mathematical relationship between contact force and auxiliary variables. For reconfigurable manipulator system, it is difficult to determine the mathematical relationship between end contact force and other auxiliary variables. To solve the problem and avoid the difficulty in observer design and convergence analysis, this study presents two kinds of decentralized adaptive force control methods based on soft sensor. One is the hybrid force/position control method based on adaptive RBF neural network estimation. The contact force is estimated by RBF neural network, and the adaptive laws of its center and width are deduced. The other is the impedance inner/ force outer loop control method based on the Fuzzy prediction reference trajectory. The end contact force is approximated by the fuzzy systems. The proposed two methods derive adaptive laws of all parameters, and are compared with the force estimation method based on the observer.

This article is organized as follows. Problem formulation, the necessity and importance for study of position and force control based on soft sensor is described in section "Introduction". In section "Reconfigurable manipulator dynamic model", the dynamic model of reconfigurable manipulator and the subsystem dynamic model at each direction are given. In section "The decentralized force controller design based on soft sensor", design and simulation of two force/position controllers based on soft sensor are proposed. The last section is the conclusion.

2 Reconfigurable manipulator dynamic model

When reconfigurable manipulator is in contact with the environment, its dynamic model with the external disturbance in the joint space is

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + \tau_f(q,\dot{q},t) = \tau - \tau_c \quad (1)$$

where $q \in R^n$ denotes the joint position; $\dot{q}$, $\ddot{q}$ are the speed and acceleration of the joint, respectively; $M(q) \in R^{n\times n}$ is the inertia matrix; $C(q,\dot{q})\dot{q} \in R^n$ donates the Centripetal and Coriolis torques; $G(q) \in R^n$ is the gravitational torque vector; $\tau \in R^n$ is the control torque; $\tau_c \in R^n$ is the torque vector exerted by the manipulator on the environment; $\tau_f(q,\dot{q},t) \in R^n$ is the external disturbance.

Consider the following equations [20]

$$\begin{cases} \dot{X} = J\dot{q} \\ \ddot{X} = \dot{J}\dot{q} + J\ddot{q} \\ \tau = J^T F \end{cases}$$

where J is the Jacobian matrix; F and X are the contact force and position of the task space, respectively.

With the workspace position X as the variable, the equation (1) is written as

$$M_x\ddot{X} + C_x\dot{X} + G_x + F_f = F - F_C \qquad (2)$$

where

$$M_x = J^{-T}M(q)J^{-1}$$

$$C_x = J^{-T}[C(q,\dot{q}) - M(q)J^{-1}\dot{J}]J^{-1}$$

$$G_x = J^{-T}G(q)$$

$$F_f = J^{-T}\tau_f(q,\dot{q},t)$$

$$F_c = J^{-T}\tau_c$$

The model of reconfigurable manipulator is decomposed at each direction, and the dynamic model of the subsystem j is as follows

$$M_j(x_j)\ddot{x}_j + C_j(x_j,\dot{x}_j)\dot{x}_j + G_j(x_j) + F_{fj}(x_j,\dot{x}_j,t) + Z_j(X,\dot{X},\ddot{X}) = F_j - F_{cj} \qquad (3)$$

where x_j is the jth element of the vector X and

$$Z_j(X,\dot{X},\ddot{X}) = \left\{\sum_{m=1,m\neq j}^{n} M_{jm}(X)\ddot{x}_m + [M_{jj}(X) - M_j(x_j)]\ddot{x}_j\right\} + \left\{\sum_{m=1,m\neq j}^{n} C_{jm}(X,\dot{X})\dot{x}_m + [C_{jj}(X,\dot{X}) - C_j(x_j,\dot{x}_j)]\dot{x}_j\right\} + [\overline{G}_j(x_j) - G_j(x_j)]$$

is coupled interconnection between the subsystems.

In the premise of without wrist force sensor, the next task is to design the controller based on soft sensor for the subsystem equation (3) so as to realize the position and force control of reconfigurable manipulator in the constrained space.

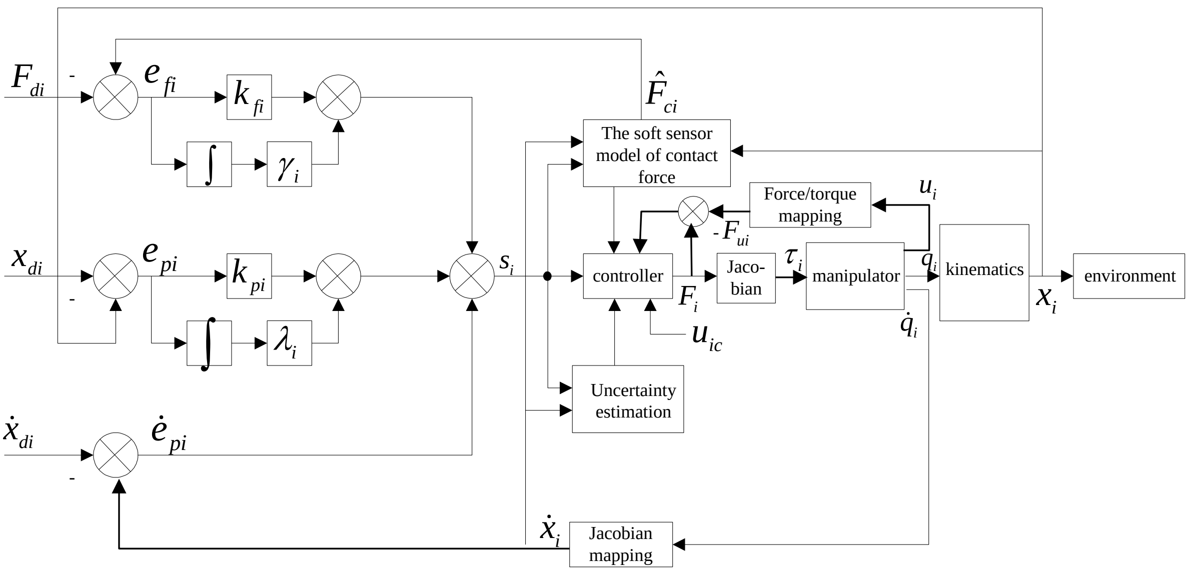


Figure1. Control block diagram of decentralized hybrid force/position controller

3 The decentralized force controller design based on soft sensor

3.1 The design of decentralized hybrid force/position controller based on adaptive RBFNN soft sensor model

3.1.1 Controller design

The advantage of the hybrid force/position controller is able to directly control contact force. In this part, PI control algorithm based on the force error is adopted to control force and PID control algorithm based on the position error is used in the position control. In the absence of wrist force sensor, the soft sensor model of the contact force is established based on adaptive RBFNN, and subsystem uncertainty and coupling interconnection are also estimated by using RBFNN. The control block diagram of decentralized hybrid force/position controller is shown in Figure1.

The force error and position error of the subsystems are defined as follows:

$$e_{fj} = \hat{F}_{cj} - F_{dj}, e_{pj} = x_j - x_{dj}$$

where $\hat{F}_{cj}$ is the estimate value of F_{cj}, x_{dj} and F_{dj} are respectively the desired position and contact force.

Letting

$$x_{jr} = \dot{x}_{dj} - k_{pj}e_{pj} - \lambda_j \int_0^t e_{pj} d\tau - k_{fj}e_{fj} - \gamma_j \int_0^t e_{fj} d\tau$$

$$s_j = \dot{x}_j - x_{jr}$$

We have

$$s_j = \dot{x}_j - x_{jr} = \dot{e}_{pj} + k_{pj}e_{pj} + \lambda_j \int_0^t e_{pj} d\tau + k_{fj}e_{fj} + \gamma_j \int_0^t e_{fj} d\tau$$

So

$$\dot{s}_j = \ddot{x}_j - \dot{x}_{jr} = \ddot{e}_{pj} + k_{pj}\dot{e}_{pj} + \lambda_j e_{pj} + k_{fj}\dot{e}_{fj} + \gamma_j e_{fj} \tag{4}$$

Bringing $\dot{x}_j = s_j + x_{jr}$ and $\ddot{x}_j = \dot{s}_j + \dot{x}_{jr}$ into equation (3), then equation (3) will be

$$M_j(x_j)(\dot{s}_j + \dot{x}_{jr}) + C_j(x_j, \dot{x}_j)(s_j + x_{jr}) + G_j(x_j) + F_{fj}(x_j, \dot{x}_j, t) + Z_j(X, \dot{X}, \ddot{X}) = F_j - F_{cj}$$

The above equation is written as

$$M_j(x_j)\dot{s}_j + C_j(x_j, \dot{x}_j)s_j + h_j(s_j) = F_j - F_{cj}(x_j, \dot{x}_j)$$

where

$$h_j = M_j(x_j)\dot{x}_{jr} + C_j(x_j, \dot{x}_j)x_{jr} + G_j(x_j) + F_{fj}(x_j, \dot{x}_j, t) + Z_j(X, \dot{X}, \ddot{X})$$

We introduce a decentralized control law that is described by

$$F_j = \hat{F}_{cj}(x_j, \dot{x}_j, |s_j|) + \hat{h}_j(|x_j|, s_j) - m_j s_j + u_{jc} + u_{j\tau} \tag{5-a}$$

$$u_{jc} = -(E_{1f} + E_{1h})sign(s_j^T) \tag{5-b}$$

$$u_{j\tau} = -k_{j\tau}|F_j - F_{uj}|sign(s_j^T) \tag{5-c}$$

where u_{jc} is the approximation error compensation; $u_{j\tau}$ is the joint torque compensation; E_{1f} and E_{1h} are the error upper bounds of the contact force $F_{cj}(x_j, \dot{x}_j)$ and $h_j(s_j)$,respectively; $k_{j\tau}$ and m_j are the positive constants; F_{uj} is the output mapping of the joint torque sensor; $\hat{F}_{cj}(x_j, \dot{x}_j, |s_j|)$ and $\hat{h}_j(|x_j|, s_j)$ are respectively the estimate values of $F_{cj}(x_j, \dot{x}_j)$ and $h_j(s_j)$ that can be expressed by using adaptive RBFNN

$$\hat{F}_{cj}(x_j, \dot{x}_j, |s_j|) = \hat{W}_{jfc}^T \xi_{jfc}(x_j, \dot{x}_j, |s_j|)$$

$$\hat{h}_j(|x_j|, s_j) = \hat{W}_{jh}^T \xi_{jh}(|x_j|, s_j)$$

where $\hat{W}_{jfc}, \hat{W}_{jh}$ are the weight vectors; $\xi_{jh}(|x_j|, s_j)$ and $\xi_{jfc}(x_j, \dot{x}_j, |s_j|)$ are the radial basis functions (Internal structure of RBFNN for estimating contact force refers to **Appendix I**).

The following adaptive laws of the parameters are obtained

$$\dot{\hat{W}}_{jfc} = \eta_{j1} s_j^T \hat{\xi}_{jfc}(x_j, \dot{x}_j, |s_j|) \tag{6-a}$$

$$\dot{\hat{W}}_{jh} = \eta_{j2} s_j^T \hat{\xi}_{jh}(|x_j|, s_j) \tag{6-b}$$

$$\dot{\hat{c}}_{jfc} = \eta_{j3} s_j^T \frac{\partial \xi_{jfc}}{\partial \hat{c}_{jfc}} \hat{W}_{jfc}(x_j, \dot{x}_j, |s_j|) \tag{6-c}$$

$$\dot{\hat{b}}_{jfc} = \eta_{j4} s_j^T \frac{\partial \xi_{jfc}}{\partial \hat{b}_{jfc}} \hat{W}_{jfc}(x_j, \dot{x}_j, |s_j|) \tag{6-d}$$

$$\dot{\hat{c}}_{jh} = \eta_{j5} s_j^T \frac{\partial \xi_{jh}}{\partial \hat{c}_{jh}} \hat{W}_{jh}(|x_j|, s_j) \tag{6-e}$$

$$\dot{\hat{b}}_{jh} = \eta_{j6} s_j^T \frac{\partial \xi_{jh}}{\partial \hat{b}_{jh}} \hat{W}_{jh}(|x_j|, s_j) \tag{6-f}$$

where $\hat{c}_{jfc}, \hat{c}_{jh}$ and $\hat{b}_{jfc}, \hat{b}_{jh}$ are centers and widths of the radial basis function $\hat{\xi}_{jfc}(x_j, \dot{x}_j, |s_j|)$ and $\hat{\xi}_{jh}(|x_j|, s_j)$, respectively; $\eta_{j1}, \eta_{j2}, \eta_{j3}, \eta_{j4}, \eta_{j5}, \eta_{j6}$ are the positive constants.

Property 1. For the scalar function $M_j(q_j)$ and $C_j(q_j, \dot{q}_j)$, there is the following equation [21]:

$$s_j^T[\dot{M}_j(q_j) - 2C_j(q_j, \dot{q}_j)]s_j = 0 \quad \forall s_j \in R$$

Assumption 1. Approximation errors of RBFNN are assumed to be bounded by $|\varepsilon_{1jf}| \le E_{1f}$, $|\varepsilon_{1jh}| \le E_{1h}$, where ε_{1jf} and ε_{1jh} are the approximation errors of $F_{cj}(x_j, \dot{x}_j)$ and $h_j(s_j)$, respectively.

Theorem 1. For the subsystem dynamic model described by equation (3), if the decentralized control laws such as equation (5) and adaptive laws of the parameters such as equation (6) are applied, the position error and force error of reconfigurable manipulator system will asymptotically converge to zero in the constrained space.

Proof. The Lyapunov function is defined by

$$V = \sum_{j=1}^{n} V_j$$

where

$$V_j = \frac{1}{2} s_j^T M_j s_j + \frac{1}{2\eta_{j1}} \tilde{W}_{jfc}^T \tilde{W}_{jfc} + \frac{1}{2\eta_{j2}} \tilde{W}_{jh}^T \tilde{W}_{jh} + \frac{1}{2\eta_{j3}} \tilde{c}_{jfc}^T \tilde{c}_{jfc} + \frac{1}{2\eta_{j4}} \tilde{b}_{jfc}^T \tilde{b}_{jfc} + \frac{1}{2\eta_{j5}} \tilde{c}_{jh}^T \tilde{c}_{jh} + \frac{1}{2\eta_{j6}} \tilde{b}_{jh}^T \tilde{b}_{jh}$$

where $\tilde{W}_{jfc} = W_{jfc} - \hat{W}_{jfc}$, and the other error variables are like this.

The time derivative of Lyapunov function V_j is

$$\begin{aligned}
\dot{V}_j &= \frac{1}{2} s_j^T \dot{M}_j s_j + s_j^T M_j \dot{s}_j - \frac{1}{\eta_{j1}} \tilde{W}_{jfc}^T \dot{\hat{W}}_{jfc} - \frac{1}{\eta_{j2}} \tilde{W}_{jh}^T \dot{\hat{W}}_{jh} \\
&\quad - \frac{1}{\eta_{j3}} \tilde{c}_{jfc}^T \dot{\hat{c}}_{jfc} - \frac{1}{\eta_{j4}} \tilde{b}_{jfc}^T \dot{\hat{b}}_{jfc} - \frac{1}{\eta_{j5}} \tilde{c}_{jh}^T \dot{\hat{c}}_{jh} - \frac{1}{\eta_{j6}} \tilde{b}_{jh}^T \dot{\hat{b}}_{jh} \\
&= \frac{1}{2} s_j^T \dot{M}_j s_j + s_j^T (F_j - F_{cj} - C_j s_j - h_j) - \frac{1}{\eta_{j1}} \tilde{W}_{jfc}^T \dot{\hat{W}}_{jfc} \\
&\quad - \frac{1}{\eta_{j2}} \tilde{W}_{jh}^T \dot{\hat{W}}_{jh} - \frac{1}{\eta_{j3}} \tilde{c}_{jfc}^T \dot{\hat{c}}_{jfc} - \frac{1}{\eta_{j4}} \tilde{b}_{jfc}^T \dot{\hat{b}}_{jfc} - \frac{1}{\eta_{j5}} \tilde{c}_{jh}^T \dot{\hat{c}}_{jh} \\
&\quad - \frac{1}{\eta_{j6}} \tilde{b}_{jh}^T \dot{\hat{b}}_{jh} \\
&= \frac{1}{2} s_j^T (\dot{M}_j - 2C_j) s_j + s_j^T (F_j - F_{cj} - h_j) \\
&\quad - \frac{1}{\eta_{j1}} \tilde{W}_{jfc}^T \dot{\hat{W}}_{jfc} - \frac{1}{\eta_{j2}} \tilde{W}_{jh}^T \dot{\hat{W}}_{jh} - \frac{1}{\eta_{j3}} \tilde{c}_{jfc}^T \dot{\hat{c}}_{jfc} \\
&\quad - \frac{1}{\eta_{j4}} \tilde{b}_{jfc}^T \dot{\hat{b}}_{jfc} - \frac{1}{\eta_{j5}} \tilde{c}_{jh}^T \dot{\hat{c}}_{jh} - \frac{1}{\eta_{j6}} \tilde{b}_{jh}^T \dot{\hat{b}}_{jh}
\end{aligned}$$

Using property 1 and control law equation (5), it is easy to show that

$$\begin{aligned}
\dot{V}_j &= s_j^T [\hat{F}_{cj} + \hat{h}_j - m_j s_j + u_{jc} + u_{j\tau} - F_{cj} - h_j] \\
&\quad - \frac{1}{\eta_{j1}} \tilde{W}_{jfc}^T \dot{\hat{W}}_{jfc} - \frac{1}{\eta_{j2}} \tilde{W}_{jh}^T \dot{\hat{W}}_{jh} - \frac{1}{\eta_{j3}} \tilde{c}_{jfc}^T \dot{\hat{c}}_{jfc} \\
&\quad - \frac{1}{\eta_{j4}} \tilde{b}_{jfc}^T \dot{\hat{b}}_{jfc} - \frac{1}{\eta_{j5}} \tilde{c}_{jh}^T \dot{\hat{c}}_{jh} - \frac{1}{\eta_{j6}} \tilde{b}_{jh}^T \dot{\hat{b}}_{jh} \\
&= -m_j s_j^T s_j + s_j^T u_{jc} + s_j^T u_{j\tau} + -s_j^T \tilde{F}_{cj} - s_j^T \tilde{h}_j \\
&\quad - \frac{1}{\eta_{j1}} \tilde{W}_{jfc}^T \dot{\hat{W}}_{jfc} - \frac{1}{\eta_{j2}} \tilde{W}_{jh}^T \dot{\hat{W}}_{jh} - \frac{1}{\eta_{j3}} \tilde{c}_{jfc}^T \dot{\hat{c}}_{jfc} \\
&\quad - \frac{1}{\eta_{j4}} \tilde{b}_{jfc}^T \dot{\hat{b}}_{jfc} - \frac{1}{\eta_{j5}} \tilde{c}_{jh}^T \dot{\hat{c}}_{jh} - \frac{1}{\eta_{j6}} \tilde{b}_{jh}^T \dot{\hat{b}}_{jh}
\end{aligned}$$

For an arbitrary function $f_j = W_k^T \xi_k + \varepsilon_j$, its estimate value is $\hat{f}_j = \sum_{k=1}^{5} \hat{W}_{jk} \hat{\xi}_{jk} = \hat{W}_k^T \hat{\xi}_k$, where ε_j is the estimate error and $\hat{f}_j$ is the adaptive RBFNN estimate value of f_j, then

$$\begin{aligned}
\tilde{f}_j &= f_j - \hat{f}_j \\
&= W_k^T \xi_k + \varepsilon_j - \hat{W}_k^T \hat{\xi}_k \\
&= (\hat{W}_k + \tilde{W}_k)^T (\hat{\xi}_k + \tilde{\xi}_k) + \varepsilon_j - \hat{W}_k^T \hat{\xi}_k \\
&= \hat{W}_k^T \tilde{\xi}_k + \tilde{W}_k^T \hat{\xi}_k + \tilde{W}_k^T \tilde{\xi}_k + \varepsilon_j \\
&= \hat{W}_k^T \tilde{\xi}_k + \tilde{W}_k^T \hat{\xi}_k + \varepsilon_{1j}
\end{aligned} \tag{7}$$

where $\varepsilon_{1j} = \tilde{W}_k^T \tilde{\xi}_k + \varepsilon_j + \hat{W}_k^T o(h)$.

According to Taylor series expansion, we can obtain

$$\tilde{\xi}_k = \frac{\partial \xi_k}{\partial \hat{c}_k} \cdot \tilde{c}_k + \frac{\partial \xi_k}{\partial \hat{b}_k} \cdot \tilde{b}_k \qquad (8)$$

By analogy with equation (7) and equation (8), we get

$$\begin{aligned}\dot{V}_j = & -m_j s_j^T s_j + s_j^T u_{jc} + s_j^T u_{j\tau} - s_j^T [\tilde{W}_{jfc}^T \hat{\xi}_{jfc} + \varepsilon_{1jf} + \\ & \hat{W}_{jfc}^T (\frac{\partial \xi_{jfc}}{\partial \hat{c}_{jfc}} \cdot \tilde{c}_{jfc} + \frac{\partial \xi_{jfc}}{\partial \hat{b}_{jfc}} \cdot \tilde{b}_{jfc})] - s_j^T [\tilde{W}_{jh}^T \hat{\xi}_{jh} + \\ & \varepsilon_{1jh} + \hat{W}_{jh}^T (\frac{\partial \xi_{jh}}{\partial \hat{c}_{jh}} \cdot \tilde{c}_{jh} + \frac{\partial \xi_{jh}}{\partial \hat{b}_{jh}} \cdot \tilde{b}_{jh})] - \frac{1}{\eta_{j1}} \tilde{W}_{jfc}^T \dot{\hat{W}}_{jfc} \\ & - \frac{1}{\eta_{j2}} \tilde{W}_{jh}^T \dot{\hat{W}}_{jh} - \frac{1}{\eta_{j3}} \tilde{c}_{jfc}^T \dot{\hat{c}}_{jfc} - \frac{1}{\eta_{j4}} \tilde{b}_{jfc}^T \dot{\hat{b}}_{jfc} - \frac{1}{\eta_{j5}} \tilde{c}_{jh}^T \dot{\hat{c}}_{jh} \\ & - \frac{1}{\eta_{j6}} \tilde{b}_{jh}^T \dot{\hat{b}}_{jh}\end{aligned}$$

Since $\hat{W}_{jfc}^T \dfrac{\partial \xi_{jfc}}{\partial \hat{c}_{jfc}} \cdot \tilde{c}_{jfc} = \tilde{c}_{jfc}^T \dfrac{\partial \xi_{jfc}}{\partial \hat{c}_{jfc}} \hat{W}_{jfc}$ and adaptive laws of the parameters in the equation (6) are introduced into above equation, we get

$$\begin{aligned}\dot{V}_j & = -m_j s_j^T s_j + s_j^T u_{jc} + s_j^T u_{j\tau} - s_j^T \varepsilon_{1jf} - s_i^T \varepsilon_{1jh} \\ & \le -m_j s_j^T s_j + s_j^T u_{jc} + s_j^T u_{j\tau} + |s_j^T| E_{1f} + |s_j^T| E_{1h}\end{aligned}$$

According to the equation (5-c), the above inequality can be written

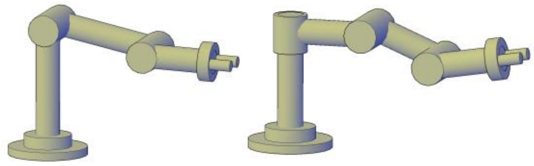
$$\dot{V}_j \le -m_j s_j^T s_j + s_j^T u_{jc} + |s_j^T| E_{1f} + |s_j^T| E_{1h}$$

Applying equation (5-b), it is easy to obtain $\dot{V}_j \le -m_j s_j^2$, namely $\dot{V} = \sum_{j=1}^{n} \dot{V}_j \le \sum_{j=1}^{n} - m_j s_j^2$.

Because $\int_0^\infty \sum_{j=1}^{n} m_j s_j^2 \le -\int_0^\infty \dot{V} dt = V(0) - V(\infty) < \infty$, it is obvious that $s_j \in L_2$. By equation (4) can be known $\dot{s}_j \in L_\infty$.According to Babalat lemma [22], $\lim_{t \to \infty} s_j(t) = 0$, and this means that the theorem is proved.

3.1.2 Simulation results

The designed controller is applied to 2-DOF planar reconfigurable manipulator in the Figure 2(a).

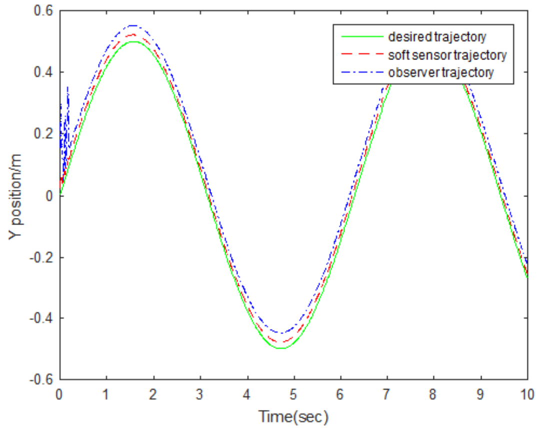


(a) 2-DOF planar manipulator (b) 3-DOF reconfigurable manipulator

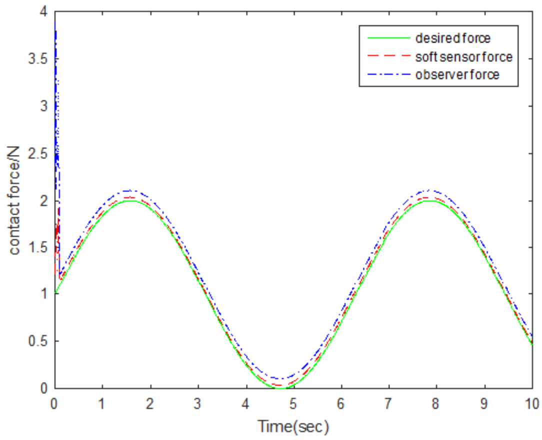
Figure 2. Reconfigurable manipulator configurations

The desired position trajectory is defined as $y_d = 0.5 \sin t$ in the Y direction, and the desired force is $f_d = (1 + \sin t)\mathrm{N}$ in the X direction.

To show the efficiency of the proposed method in improving the tracking accuracy, the observer in reference [15] is also employed in the simulation for comparison. The simulation results under the proposed soft sensor and the observer are depicted in Figures 3.



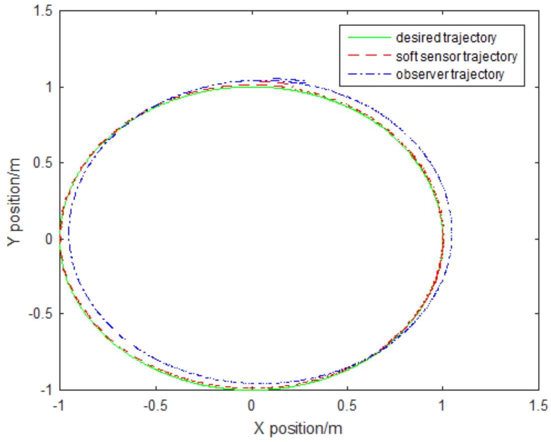
(a) Y direction position tracking



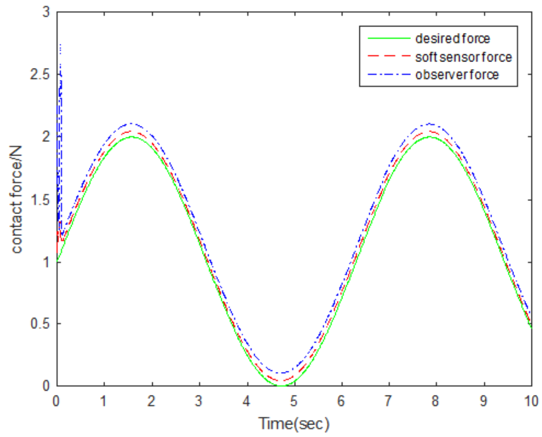
(b) X direction force tracking

Figure 3. Force and position tracking of 2-DOF planar manipulator

The 3-DOF reconfigurable manipulator is shown in Figure 2(b). The contact force is controlled in Z direction of the constrained surface, and the position trajectories are controlled in Y and X directions. Given the desired force $f_d = (1 + \sin t)\mathrm{N}$, and desired trajectories are set to be $x_d = \sin(t)$, $y_d = \cos(t)$. The simulation results are shown in Figure 4.



(a) X-Y plane position tracking



(b) Z direction force tracking

Figure 4. Force and position tracking of 3-DOF manipulator

It is observed from Figures 3 and 4 that in the initial stage of the observer, the observer lacks the knowledge of the subsystem dynamics model, so its tracking error is relatively large during the first 0.5 s. In the following tracking process, the observer is easily affected by the Jacobi matrix transformation and the parameters of the proposed soft sensor method are adjusted in real time according to the force error and the position error，so the simulation accuracy of the proposed soft sensor method is better than the observer method.

It is worth noting that this method can cause certain impact force when the manipulator moves from free space to constrained space, so it is only suitable for position and force control in constrained space.

3.2 The design of impedance inner/ force outer loop controller based on adaptive fuzzy soft sensor model

The impedance control method can realize indirectly force control by adjusting the reference position. The soft sensor model of the contact force is established based on adaptive fuzzy system in the proposed method, and corrected value of the reference trajectory for the impedance inner controller is provided by output of the force outer loop controller based on the fuzzy prediction.

3.2.1 The reference trajectory algorithm based on the fuzzy prediction

The algorithm consists of the following parts:

1) The reference trajectory that makes the current output value gradually transit to the setting value. The equation is written as

$$F_{dj}(k+i) = \alpha^i \times \hat{F}_{cj} + (1-\alpha^i) \times F_{dj}$$

where α is the softness coefficient, k is the sampling time, i is the predictive step.

2) The prediction model is chosen as

$$B_d \dot{X} + K_d (X - X_r) = F_d - F_c$$

where B_d and K_d are the desired damping and position stiffness matrices, respectively. They are replaced by the b_d and k_d in the subsystem; X is the position of the manipulator; X_r is the reference trajectory of the impedance inner controller. The selected model is equivalent to

$$F_{cj}(k+i) = F_{dj}(k+i) - b_d \dot{x}_j(k) - k_d[x_j(k) - x_{rj}(k)]$$

3) The prediction output (equivalent to the feedback correction) is

$$F_{pj}(k+i) = F_{cj}(k+i) + \beta_i[\hat{F}_{cj} - F_{cj}(k)]$$

where β_i is the correction coefficient.

3.2.2 Controller design and prove

The block diagram of impedance control system is shown in Figure 5.

The force error and position error are defined as

$$e_{fj} = \hat{F}_{cj} - F_{dj}$$

$$e_{pj} = x_j - x_{dj}$$

They are introduced into the first order filter

$$\dot{\mu}_j + k_j \mu_j = \eta_j e_{fj}$$

$$\dot{p}_j + k_j p_j = \lambda_j e_{pj}$$

where k_j, η_j and λ_j are the positive constants, μ_j and p_j are the filter outputs.

σ_j is defined by $\sigma_j = \dot{e}_{pj} + p_j + \mu_j$, namely $p_j = \sigma_j - \dot{e}_{pj} - \mu_j$. The time derivative of σ_j is given by

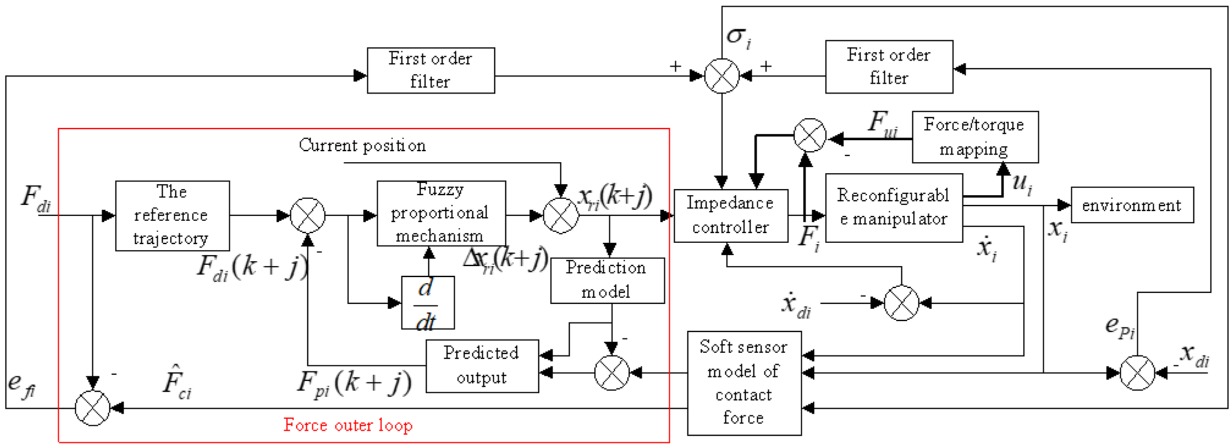


Figure 5. Block diagram of impedance control system

$$\begin{aligned}
\dot{\sigma}_j &= \ddot{e}_{pj} + \dot{p}_j + \dot{\mu}_j \\
&= \ddot{e}_{pj} + \lambda_j e_{pj} - k_j p_j + \eta_j e_{fj} - k_j \mu_j \\
&= \ddot{e}_{pj} + \lambda_j e_{pj} - k_j(\sigma_j - \dot{e}_{pj} - \mu_j) + \eta_j e_{fj} - k_j \mu_j \\
&= \ddot{e}_{pj} + \lambda_j e_{pj} + k_j \dot{e}_{pj} - k_j \sigma_j + \eta_j e_{fj}
\end{aligned}$$

The above equation is rewritten as

$$\ddot{e}_{pj} + k_j \dot{e}_{pj} + \lambda_j e_{pj} = \dot{\sigma}_j + k_j \sigma_j - \eta_j e_{fj} \qquad (9)$$

By choosing $\begin{cases} k_j = m_d^{-1} b_d \\ \lambda_j = m_d^{-1} k_d \\ \eta_j = m_d^{-1} \end{cases}$, $\dot{\sigma}_j = 0$ and $\sigma_j = 0$,

equation (9) is identical to the target impedance as follows equation (10).

$$m_d \ddot{e}_{pj} + b_d \dot{e}_{pj} + k_d e_{pj} = -e_{fj} \qquad (10)$$

where m_d is the desired inertia.

Differentiating σ_j with respect to time, we have

$$\begin{aligned}
\dot{\sigma}_j &= \ddot{e}_{pj} + \dot{p}_j + \dot{\mu}_j \\
&= M_j^{-1}[F_j - F_{cj} - C_j(x_j, \dot{x}_j)\dot{x}_j - G_j(x_j) \\
&\quad - F_{fj}(x_j, \dot{x}_j, t) - Z_j(X, \dot{X}, \ddot{X})] - \ddot{x}_{dj} \\
&\quad + \dot{p}_j + \dot{\mu}_j
\end{aligned} \qquad (11)$$

The control law is obtained as:

$$\begin{aligned}
F_j &= \hat{F}_{cj}(x_j, \dot{x}_j, |\sigma_j|) + \hat{C}_j(x_j, \dot{x}_j)\dot{x}_j + \hat{G}_j(x_j) + \\
&\quad \hat{F}_{fj}(x_j, \dot{x}_j, t) + \hat{Z}_j(X, \dot{X}, \ddot{X}) + \\
&\quad \hat{M}_j(\ddot{x}_{dj} - \dot{p}_j - \dot{\mu}_j) - m_j \sigma_j + u_{jc} + u_{ja} \\
&= \hat{M}_j \ddot{x}_{jeq} + \hat{C}_j \dot{x}_{jeq} + \hat{G}_j(x_j) + \hat{F}_{fj}(x_j, \dot{x}_j, t) + \\
&\quad \hat{Z}_j(X, \dot{X}, \ddot{X}) + \hat{F}_{cj} - m_j \sigma_j + u_{jc} + u_{ja}
\end{aligned} \qquad (12\text{-a})$$

$$\begin{aligned}
u_{jc} &= -(d_{jm}|\ddot{x}_{jeq}| + d_{jc}|\dot{x}_{jeq}| + d_{jg} + \\
&\quad d_{jf} + d_{jz} + d_{jfc}) sign(\sigma_j^T)
\end{aligned} \qquad (12\text{-b})$$

$$u_{ja} = -k_{ja}|F_j - F_{uj}| sign(\sigma_j^T) \qquad (12\text{-c})$$

where

$$\sigma_j = 0 \Rightarrow \dot{x}_{jeq} = \dot{x}_{dj} - p_j - \mu_j$$

$$\dot{\sigma}_j = 0 \Rightarrow \ddot{x}_{jeq} = \ddot{x}_{dj} - \dot{p}_j - \dot{\mu}_j$$

$d_{jm}, d_{jc}, d_{jg}, d_{jf}, d_{jz}, d_{jfc}$ are error upper bounds of of $M_j(x_j), C_j(x_j, \dot{x}_j)$, $G_j(x_j), F_{fj}(x_j, \dot{x}_j, t)$, $Z_j(X, \dot{X}, \ddot{X})$ and F_{cj}, respectively; $\hat{F}_{cj}(x_j, \dot{x}_j, |\sigma_j|)$, $\hat{M}_j(x_j), \hat{C}_j(x_j, \dot{x}_j), \hat{G}_j(x_j), \hat{F}_{fj}(x_j, \dot{x}_j, t), \hat{Z}_j(X, \dot{X}, \ddot{X})$ are the estimates of $F_{cj}, M_j(x_j), C_j(x_j, \dot{x}_j)$, $G_j(x_j)$, $F_{fj}(x_j, \dot{x}_j, t)$ and $Z_j(X, \dot{X}, \ddot{X})$, respectively; F_{uj} is the output mapping of the joint torque sensor; u_{jc} is the compensation of the estimation error ; u_{ja} is the compensation of the joint torque measured value; k_{ja} is the positive constant.

The fuzzy system representations are described by

$$\hat{F}_{cj}(x_j, \dot{x}_j, |\sigma_j|) = \hat{\theta}_{jfc}^T \xi_{jfc}(x_j, \dot{x}_j, |\sigma_j|)$$

$$\hat{M}_j(x_j) = \hat{\theta}_{jm}^T \xi_{jm}(x_j)$$

$$\hat{C}_j(x_j, \dot{x}_j) = \hat{\theta}_{jc}^T \xi_{jc}(x_j, \dot{x}_j)$$

$$\hat{G}_j(x_j) = \hat{\theta}_{jg}^T \xi_{jg}(x_j)$$

$$\hat{F}_{fj}(x_j, \dot{x}_j, t) = \hat{\theta}_{fj}^T \xi_{fj}(x_j, \dot{x}_j, t_j)$$

$$\hat{Z}_j(X, \dot{X}, \ddot{X}) = \hat{\theta}_{jz}^T \xi_{jz}(X, \dot{X}, \ddot{X})$$

where $\hat{\theta}_{jfc}$, $\hat{\theta}_{jm}$, $\hat{\theta}_{jc}$, $\hat{\theta}_{jg}$, $\hat{\theta}_{fj}$ and $\hat{\theta}_{jZ}$ are the adjustable parameter vectors, respectively; $\xi_{jfc}(x_j, \dot{x}_j, |\sigma_j|)$, $\xi_{jm}(x_j)$, $\xi_{jc}(x_j, \dot{x}_j)$, $\xi_{jg}(x_j)$, $\xi_{fj}(x_j, \dot{x}_j, t_j)$ and $\xi_{jz}(X, \dot{X}, \ddot{X})$ are the fuzzy basis function vectors , respectively(Membership function of fuzzy system for estimating contact force refers to **Appendix II**).

The adaptive laws of the parameters are

$$\dot{\hat{\theta}}_{jm} = \eta_{j1} \sigma_j^T \xi_{jm} \ddot{x}_{jeq} \quad (13\text{-a})$$

$$\dot{\hat{\theta}}_{jc} = \eta_{j2} \sigma_j^T \xi_{jc} \dot{x}_{jeq} \quad (13\text{-b})$$

$$\dot{\hat{\theta}}_{jg} = \eta_{j3} \sigma_j^T \xi_{jg} \quad (13\text{-c})$$

$$\dot{\hat{\theta}}_{jz} = \eta_{j4} \sigma_j^T \xi_{jz} \quad (13\text{-d})$$

$$\dot{\hat{\theta}}_{jfc} = \eta_{j5} \sigma_j^T \xi_{jfc} \quad (13\text{-e})$$

$$\dot{\hat{\theta}}_{fj} = \eta_{j6} \sigma_j^T \xi_{fj} \quad (13\text{-f})$$

where η_{j1} , η_{j2} , η_{j3} , η_{j4} , η_{j5} , η_{j6} are the positive constants.

Assumption 2. Approximation errors of the fuzzy system are assumed to be bounded by $|\varepsilon_{jm}| \le d_{jm}$, $|\varepsilon_{jc}| \le d_{jc}$, $|\varepsilon_{jg}| \le d_{jg}$, $|\varepsilon_{fj}| \le d_{fj}$, $|\varepsilon_{jz}| \le d_{jz}$, $|\varepsilon_{jfc}| \le d_{jfc}$,where ε_{jm}, ε_{jc}, ε_{jg}, ε_{fj}, ε_{jz} and ε_{jfc} are approximation errors of $M_j(x_j)$, $C_j(x_j, \dot{x}_j)$, $G_j(x_j)$, $F_{fj}(x_j, \dot{x}_j, t)$, $Z_j(X, \dot{X}, \ddot{X})$ and F_{cj} , respectively.

Theorem 2. For the subsystem dynamic model described by equation (3), reconfigurable manipulator system achieves the target impedance equation (10) with the decentralized control law equation (12) and the adaptive laws of the parameters equation (13).

Proof. Lyapunov function is chosen as

$$V = \sum_{j=1}^{n} V_j$$

where

$$V_j = \frac{1}{2} M_j \sigma_j^2 + \frac{1}{2\eta_{j1}} \tilde{\theta}_{jm}^T \tilde{\theta}_{jm} + \frac{1}{2\eta_{j2}} \tilde{\theta}_{jc}^T \tilde{\theta}_{jc} + \frac{1}{2\eta_{j3}} \tilde{\theta}_{jg}^T \tilde{\theta}_{jg} + \frac{1}{2\eta_{j4}} \tilde{\theta}_{jz}^T \tilde{\theta}_{jz} + \frac{1}{2\eta_{j5}} \tilde{\theta}_{jfc}^T \tilde{\theta}_{jfc} + + \frac{1}{2\eta_{j6}} \tilde{\theta}_{fj}^T \tilde{\theta}_{fj}$$

Differentiating V_j with respect to time, then

$$\begin{aligned}
\dot{V}_j &= \frac{1}{2} \sigma_j^T \dot{M}_j \sigma_j + \sigma_j^T M_j \dot{\sigma}_j - \frac{1}{\eta_{j1}} \tilde{\theta}_{jm}^T \dot{\hat{\theta}}_{jm} - \frac{1}{\eta_{j2}} \tilde{\theta}_{jc}^T \dot{\hat{\theta}}_{jc} - \\
&\quad \frac{1}{\eta_{j3}} \tilde{\theta}_{jg}^T \dot{\hat{\theta}}_{jg} - \frac{1}{\eta_{j4}} \tilde{\theta}_{jz}^T \dot{\hat{\theta}}_{jz} - \frac{1}{\eta_{j5}} \tilde{\theta}_{jfc}^T \dot{\hat{\theta}}_{jfc} - \frac{1}{\eta_{j6}} \tilde{\theta}_{fj}^T \dot{\hat{\theta}}_{fj} \\
&= \sigma_j^T M_j \dot{\sigma}_j + \sigma_j^T C_j \sigma_j - \frac{1}{\eta_{j1}} \tilde{\theta}_{jm}^T \dot{\hat{\theta}}_{jm} - \frac{1}{\eta_{j2}} \tilde{\theta}_{jc}^T \dot{\hat{\theta}}_{jc} - \\
&\quad \frac{1}{\eta_{j3}} \tilde{\theta}_{jg}^T \dot{\hat{\theta}}_{jg} - \frac{1}{\eta_{j4}} \tilde{\theta}_{jz}^T \dot{\hat{\theta}}_{jz} - \frac{1}{\eta_{j5}} \tilde{\theta}_{jfc}^T \dot{\hat{\theta}}_{jfc} - \frac{1}{\eta_{j6}} \tilde{\theta}_{fj}^T \dot{\hat{\theta}}_{fj} \\
&= \sigma_j^T (M_j \ddot{x}_j - M_j \ddot{x}_{jeq}) + \sigma_j^T (C_j \dot{x}_j - C_j \dot{x}_{jeq}) - \frac{1}{\eta_{j1}} \tilde{\theta}_{jm}^T \dot{\hat{\theta}}_{jm} - \\
&\quad \frac{1}{\eta_{j2}} \tilde{\theta}_{jc}^T \dot{\hat{\theta}}_{jc} - \frac{1}{\eta_{j3}} \tilde{\theta}_{jg}^T \dot{\hat{\theta}}_{jg} - \frac{1}{\eta_{j4}} \tilde{\theta}_{jz}^T \dot{\hat{\theta}}_{jz} - \frac{1}{\eta_{j5}} \tilde{\theta}_{jfc}^T \dot{\hat{\theta}}_{jfc} - \frac{1}{\eta_{j6}} \tilde{\theta}_{fj}^T \dot{\hat{\theta}}_{fj} \\
&= \sigma_j^T (M_j \ddot{x}_j + C_j \dot{x}_j - M_j \ddot{x}_{jeq} - C_j \dot{x}_{jeq}) - \frac{1}{\eta_{j1}} \tilde{\theta}_{jm}^T \dot{\hat{\theta}}_{jm} \\
&\quad - \frac{1}{\eta_{j2}} \tilde{\theta}_{jc}^T \dot{\hat{\theta}}_{jc} - \frac{1}{\eta_{j3}} \tilde{\theta}_{jg}^T \dot{\hat{\theta}}_{jg} - \frac{1}{\eta_{j4}} \tilde{\theta}_{jz}^T \dot{\hat{\theta}}_{jz} \\
&\quad - \frac{1}{\eta_{j5}} \tilde{\theta}_{jfc}^T \dot{\hat{\theta}}_{jfc} - \frac{1}{\eta_{j6}} \tilde{\theta}_{fj}^T \dot{\hat{\theta}}_{fj} \\
&= \sigma_j^T [F_j - F_{cj} - G_j(x_j) - F_{fj}(x_j, \dot{x}_j, t) - Z_j(X, \dot{X}, \ddot{X}) \\
&\quad - M_j \ddot{x}_{jeq} - C_j \dot{x}_{jeq}] - \frac{1}{\eta_{j1}} \tilde{\theta}_{jm}^T \dot{\hat{\theta}}_{jm} - \frac{1}{\eta_{j2}} \tilde{\theta}_{jc}^T \dot{\hat{\theta}}_{jc} \\
&\quad - \frac{1}{\eta_{j3}} \tilde{\theta}_{jg}^T \dot{\hat{\theta}}_{jg} - \frac{1}{\eta_{j4}} \tilde{\theta}_{jz}^T \dot{\hat{\theta}}_{jz} - \frac{1}{\eta_{j5}} \tilde{\theta}_{jfc}^T \dot{\hat{\theta}}_{jfc} - \frac{1}{\eta_{j6}} \tilde{\theta}_{fj}^T \dot{\hat{\theta}}_{fj}
\end{aligned}$$

Using equation (12-a), we get

$$\begin{aligned}\dot{V}_j &= \sigma_j^T[\hat{M}_j\ddot{x}_{jeq} + \hat{C}_j\dot{x}_{jeq} + \hat{G}_j(x_j) + \hat{F}_{fj}(x_j,\dot{x}_j,t) \\ &\quad + \hat{Z}_j(X,\dot{X},\ddot{X}) + \hat{F}_{cj} - m_j\sigma_j + u_{jc} + u_{ja} - \\ &\quad F_{cj} - G_j(x_j) - F_{fj}(x_j,\dot{x}_j,t) - Z_j(X,\dot{X},\ddot{X}) - \\ &\quad M_j\ddot{x}_{jeq} - C_j\dot{x}_{jeq}] - \frac{1}{\eta_{j1}}\tilde{\theta}_{jm}^T\dot{\hat{\theta}}_{jm} - \frac{1}{\eta_{j2}}\tilde{\theta}_{jc}^T\dot{\hat{\theta}}_{jc} - \\ &\quad \frac{1}{\eta_{j3}}\tilde{\theta}_{jg}^T\dot{\hat{\theta}}_{jg} - \frac{1}{\eta_{j4}}\tilde{\theta}_{jz}^T\dot{\hat{\theta}}_{jz} - \frac{1}{\eta_{j5}}\tilde{\theta}_{jfc}^T\dot{\hat{\theta}}_{jfc} - \frac{1}{\eta_{j6}}\tilde{\theta}_{fj}^T\dot{\hat{\theta}}_{fj} \\ &= -m_j\sigma_j^2 + \sigma_j^T u_{jc} + \sigma_j^T u_{ja} + \sigma_j^T(\tilde{M}_j\ddot{x}_{jeq} + \tilde{C}_j\dot{x}_{jeq} \\ &\quad + \tilde{G}_j(x_j) + \tilde{Z}_j(X,\dot{X},\ddot{X}) + \tilde{F}_{cj} + \tilde{F}_{fj}(x_j,\dot{x}_j,t)) \\ &\quad + \sigma_j^T(-\varepsilon_{jm}\ddot{x}_{jeq} - \varepsilon_{jc}\dot{x}_{jeq} - \varepsilon_{jg} - \varepsilon_{jz} - \varepsilon_{jfc} - \varepsilon_{fj}) - \frac{1}{\eta_{j1}}\tilde{\theta}_{jm}^T\dot{\hat{\theta}}_{jm} \\ &\quad - \frac{1}{\eta_{j2}}\tilde{\theta}_{jc}^T\dot{\hat{\theta}}_{jc} - \frac{1}{\eta_{j3}}\tilde{\theta}_{jg}^T\dot{\hat{\theta}}_{jg} - \frac{1}{\eta_{j4}}\tilde{\theta}_{jz}^T\dot{\hat{\theta}}_{jz} - \frac{1}{\eta_{j5}}\tilde{\theta}_{jfc}^T\dot{\hat{\theta}}_{jfc} - \frac{1}{\eta_{j6}}\tilde{\theta}_{fj}^T\dot{\hat{\theta}}_{fj} \\ &= -m_j\sigma_j^2 + \sigma_j^T u_{jc} + \sigma_j^T u_{ja} + \sigma_j^T\tilde{\theta}_{jm}^T\xi_{jm}\ddot{x}_{jeq} + \\ &\quad \sigma_j^T\tilde{\theta}_{jc}^T\xi_{jc}\dot{x}_{jeq} + \sigma_j^T\tilde{\theta}_{jg}^T\xi_{jg} + \sigma_j^T\tilde{\theta}_{jz}^T\xi_{jz} + \\ &\quad \sigma_j^T\tilde{\theta}_{jfc}^T\xi_{jfc} + \sigma_j^T\tilde{\theta}_{fj}^T\xi_{fj} + \sigma_j^T(-\varepsilon_{jm}\ddot{x}_{jeq} - \varepsilon_{jc}\dot{x}_{jeq} \\ &\quad - \varepsilon_{jg} - \varepsilon_{jz} - \varepsilon_{jfc} - \varepsilon_{fj}) - \frac{1}{\eta_{j1}}\tilde{\theta}_{jm}^T\dot{\hat{\theta}}_{jm} - \\ &\quad \frac{1}{\eta_{j2}}\tilde{\theta}_{jc}^T\dot{\hat{\theta}}_{jc} - \frac{1}{\eta_{j3}}\tilde{\theta}_{jg}^T\dot{\hat{\theta}}_{jg} - \frac{1}{\eta_{j4}}\tilde{\theta}_{jz}^T\dot{\hat{\theta}}_{jz} - \\ &\quad \frac{1}{\eta_{j5}}\tilde{\theta}_{jfc}^T\dot{\hat{\theta}}_{jfc} - \frac{1}{\eta_{j6}}\tilde{\theta}_{fj}^T\dot{\hat{\theta}}_{fj}\end{aligned}$$

Applying equation (13) and assumption 2,

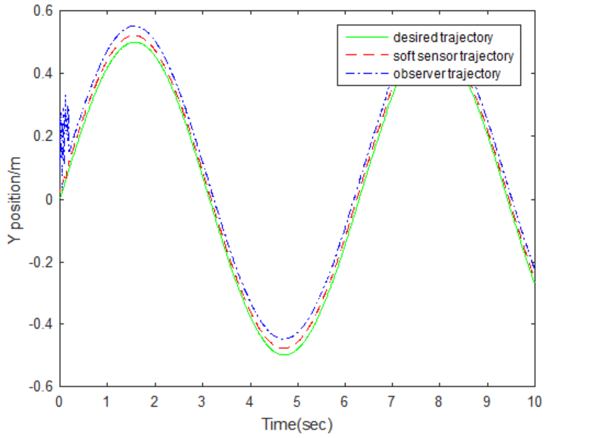
$$\begin{aligned}\dot{V}_j &= -m_j\sigma_j^2 + \sigma_j^T u_{jc} + \sigma_j^T u_{ja} + \sigma_j^T(-\varepsilon_{jm}\ddot{x}_{jeq} - \\ &\quad \varepsilon_{jc}\dot{x}_{jeq} - \varepsilon_{jg} - \varepsilon_{jz} - \varepsilon_{jfc} - \varepsilon_{fj}) \\ &\le -m_j\sigma_j^2 + \sigma_j^T u_{jc} + \sigma_j^T u_{ja} + \left|\sigma_j^T\right|(\left|\varepsilon_{jm}\right|\left|\ddot{x}_{jeq}\right| + \\ &\quad \left|\varepsilon_{jc}\right|\left|\dot{x}_{jeq}\right| + \left|\varepsilon_{jg}\right| + \left|\varepsilon_{jz}\right| + \left|\varepsilon_{jfc}\right| + \left|\varepsilon_{fj}\right|) \\ &\le -m_j\sigma_j^2 + \sigma_j^T u_{jc} + \left|\sigma_j^T\right|(d_{jm}\left|\ddot{x}_{jeq}\right| + d_{jc}\left|\dot{x}_{jeq}\right| + \\ &\quad d_{jg} + d_{jz} + d_{jfc} + d_{fj})\end{aligned}$$

Substituting equation (12-b) into inequation, it is easy to obtain $\dot{V}_j \le -m_j\sigma_j^2$, $\dot{V} = \sum_{j=1}^{n}\dot{V}_j \le \sum_{j=1}^{n} - m_j\sigma_j^2$.

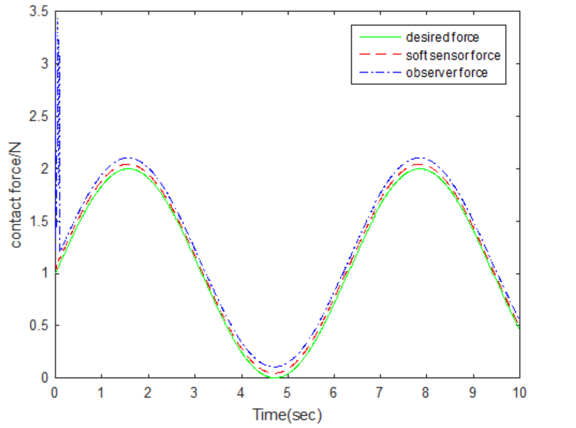
Because $\int_0^\infty \sum_{j=1}^{n} m_j\sigma_j^2 \le -\int_0^\infty \dot{V}dt = V(0) - V(\infty) < \infty$, so $\sigma_j \in L_2$. By equation (11) may be known $\dot{\sigma}_j \in L_\infty$. According to Babalat lemma [22], $\lim_{t\to\infty}\sigma_j(t) = 0$, so theorem is proved.

3.2.3 Simulation results

The designed impedance controller is applied to 2-DOF reconfigurable manipulator in the Figure 2(a). The desired force is $f_d = (1+\sin t)N$, the desired trajectory is $y_d = 0.5\sin t$. The simulation results under the proposed soft sensor and the observer are depicted in Figures 6.



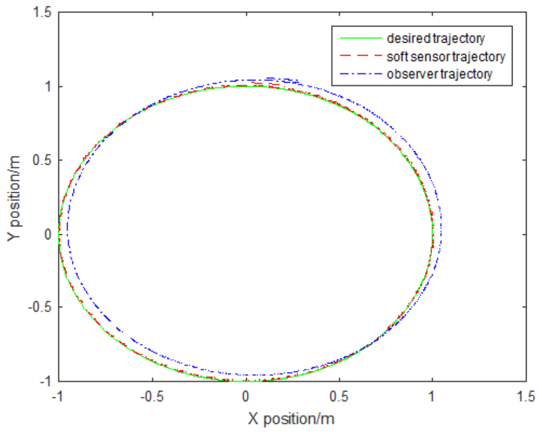
(a) Y direction position tracking



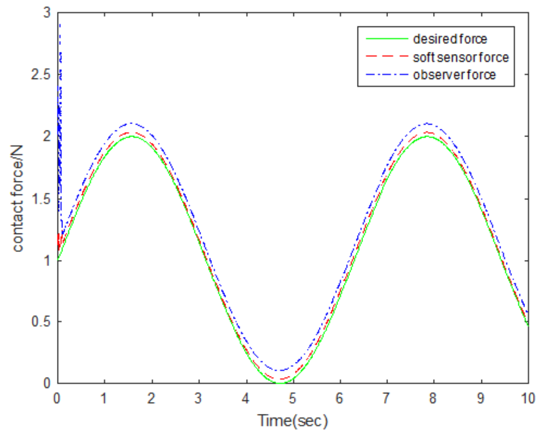
(b) X direction force tracking

Figure 6. Force and position tracking of the impedance controller for 2-DOF planar manipulator

For the 3-DOF reconfigurable manipulator in the Figure 2 (b), the desired trajectories are $x_d = \sin(t)$ and $y_d = \cos(t)$, the contact force is defined by $f_d = (1+\sin t)N$. The simulation results are shown in Figure 7.



(a) X-Y plane position tracking



(b) Z direction force tracking

Figure 7. Force and position tracking of the impedance controller for 3-DOF manipulator

Together with the tracking responses of Figures 6 and 7, it is observed that because proposed impedance inner loop control method is adaptive to adjust the parameters in equation (13), so the simulation accuracy of the proposed soft sensor method is better than the observer method. The fuzzy adjusting scaling factor and the predicting reference trajectory are suitable for the situations where the contact stiffness is unknown, and the smooth transition from free space to constrained space can also be realized.

3.3 Comparison between soft sensor method and observer force estimation method

Under the condition of that the wrist force sensor is not installed in the end of the manipulator, hybrid force/position controller based on RBFNN and impedance inner/force outer loop controller based on the fuzzy system can estimate the end contact force of reconfigurable manipulator. The two proposed methods are compared with the force estimation method based on the observer in the reference [15](Some briefed details in reference [15] refers to Appendix III), the error comparison of the 2-DOF planar reconfigurable manipulator under the two methods is shown in Table 1, and the error comparison of the 3-DOF reconfigurable manipulator under the two methods is shown in Table 2.

Table 1. Error comparison of 2-DOF planar reconfigurable manipulator

error	Method 1	Method 2	Reference [15]
Position error	0.8932	0.6271	1.5214
force error	1.5543	0.3946	5.5298

Table 2. Error comparison of 3-DOF planar reconfigurable manipulator

error	Method 1	Method 2	Reference [15]
X position error	0.2136	0.1889	1.6136
Y position error	0.3877	0.1991	1.2717
force error	0.7564	0.2654	4.2576

From the comparison of the above two tables, we can see that because of the lack of knowledge about the subsystem dynamics model in the initial stage of the observer, and the parameters of the soft sensor model are adjusted in real time according to the force error and the position error, so the position error and force error of the soft sensor force estimation method are better than the observer force estimation method.

4 Conclusions

In this paper, under the condition of reconfigurable manipulator is not installed with the wrist force sensor, two soft sensor models are established in this paper to estimate the contact force, and do not need to know the exact relationship between the contact force and the auxiliary variable. The adaptive laws of all parameters are presented. In the control process, each parameter can be adjusted timely according to the position error and force error, so as to achieve better position and force tracking performance compared with the observer. In practical application, the soft sensor method can effectively solve the problems that wrist force sensor of reconfigurable manipulator is expensive and easy to damage.

Further research works include the following aspects.

The first one is that the proposed soft sensor method will be extended to the underlying systems with the actuator faults. The key factors affecting the actuator fault are found, and the soft sensor method is used to estimate the actuator fault in real time. Second, the distributed force/position control of reconfigurable manipulator will be studied and compared with the existing decentralized control results. Sliding mode technique has a strong robustness for external disturbances of the systems, so using sliding mode technology to improve the force/position control robustness for reconfigurable manipulator could be three interesting issue. In practical applications, if the actuator is saturated, the position error and force error will be inaccurate, which will directly lead to the deviation of position and force estimation results. Therefore, the actuator saturation problem for reconfigurable manipulator will be also the key research problem in the future.

Declaration of conflicting interests

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Appendix I. Internal structure of RBF neural network for estimating contact force

The network is composed of the input layer, the hidden layer and the output layer. It contains 3 input nodes, 5 hidden layer nodes, and 1 output nodes.

The first layer: The input layer. The number of input nodes is the number of input variables.

$$f_1(i) = X = [x, \dot{x}, |s|]^T$$

In the formula, i=3 is the number of input variables, and X is the position component, which is the absolute value of the difference between the position component and its desired value.

Second layer: Hidden layer. The radial basis vector of RBF is $\xi_{fc}(j) = [h_1, h_2, h_3, h_4, h_5]^T$, $h_j(j = 1,2 \cdots 5)$ is a Gauss basis function.

$$\xi_{fc}(j) = exp(-\frac{(X - c_j)^2}{(b_j)^2})$$

In the formula, c_j is the central vector of the j node in the hidden layer, $c_j = [c_{j1}, c_{j2}, c_{j3}]^T$; b_j is the width vector of the j node of the hidden layer, and the two can all be adjusted according to the adaptive law.

The third layer: The output layer.

$$\hat{F}_c = \hat{W}_{fc}^T \xi_{fc}(j)$$

where $\hat{W}_{fc}$ is the weight vector from the hidden layer to the output layer, which can be adjusted according to the adaptive law.

Appendix II. Membership function of fuzzy system for estimating contact force

According to each input of the contact force soft sensor model, the membership function is selected as follows:

$$\mu_{F_1} = \exp(\frac{-(x+2)^\wedge 2}{0.2831}), \mu_{F_2} = \exp(\frac{-(x+1.3333)^\wedge 2}{0.2831})$$

$$\mu_{F_3} = \exp(\frac{-(x+0.6667)^\wedge 2}{0.2831}), \mu_{F_4} = \exp(\frac{-x^\wedge 2}{0.2831})$$

$$\mu_{F_5} = \exp(\frac{-(x-0.6667)^\wedge 2}{0.2831}), \mu_{F_6} = \exp(\frac{-(x-1.3333)^\wedge 2}{0.2831})$$

$$\mu_{F_7} = \exp(\frac{-(x-2)^\wedge 2}{0.2831})$$

The central averaging method is adopted for the defuzzification method.

Appendix III. Some briefed details in reference [15]

In contact with the environment, the dynamic model of the reconfigurable manipulator is as is like equation (1).

The overall block diagram of the control system is as follows：

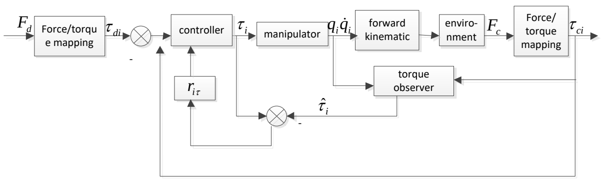

Figure 8. The overall block diagram of the control system

Each joint is regarded as a subsystem, and the dynamic model of each joint subsystem is

$$M_i(q_i)\ddot{q}_i + C_i(q_i, \dot{q}_i)\dot{q}_i + G_i(q_i) + Z_i(q, \dot{q}, \ddot{q}) + \tau_{fi} + \tau_{ci} = \tau_i \tag{14}$$

where

$$Z_i(q,\dot{q},\ddot{q}) = \left\{ \sum_{j=1, j\neq i}^{n} M_{ij}(q)\ddot{q}_j + [M_{ii}(q) - M_i(q_i)]\ddot{q}_i \right\} + \left\{ \sum_{j=1, j\neq i}^{n} C_{ij}(q,\dot{q})\dot{q}_j + [C_{ii}(q,\dot{q}) - C_i(q_i,\dot{q}_i)]\dot{q}_i \right\} + [\overline{G}_i(q) - G_i(q_i)]$$

As the subsystem has unmodeled dynamics, the equation (14) is rewritten as

$$(M_{i0} + \Delta M_{i0})\ddot{q}_i + (C_{i0} + \Delta C_{i0})\dot{q}_i + G_{i0} + \Delta G_{i0} + Z_i + \tau_{fi} + \tau_{ci} = \tau_i \tag{15}$$

where M_{i0}, C_{i0}, G_{i0} are the nominal parts, and $\Delta M_{i0}, \Delta C_{i0}, \Delta G_{i0}$ are the uncertain parts.

The equation (15) is

$$M_{i0}\ddot{q}_i + C_{i0}\dot{q}_i + G_{i0} + h_i(q,\dot{q},\ddot{q}) + \tau_{ci} = \tau_i \tag{16}$$

where

$$h_i(q,\dot{q},\ddot{q}) = \Delta M_{i0}\ddot{q}_i + \Delta C_{i0}\dot{q}_i + \Delta G_{i0} + Z_i + \tau_{fi}$$

A nonlinear joint torque observer is designed for equation (16).

$$\dot{\hat{\tau}}_i = -l_i\hat{\tau}_i + l_i(M_{i0}\ddot{q}_i + C_{i0}\dot{q}_i + G_{i0} + \hat{h}_i(q,\dot{q},\ddot{q}) + \tau_{ci}) \tag{17}$$

where l_i is the undetermined coefficient, $\hat{h}_i(q,\dot{q},\ddot{q})$ is the estimated value of $h_i(q,\dot{q},\ddot{q})$.

As the acceleration term appears in the torque observer, it is generally unknown, so an auxiliary variable is introduced to improve the observer.

The auxiliary variable is defined as follows:

$$d_i = \hat{\tau}_i - b_i \tag{18}$$

where $l_i = a_i^{-1}M_{i0}^{-1}$， $b_i = l_i M_{i0}(q_i)\dot{q}_i = a_i^{-1}\dot{q}_i$，

a_i is a constant.

Differentiating σ_j with respect to time, we have

$$\dot{d}_i = \dot{\hat{\tau}}_i - \dot{b}_i = \dot{\hat{\tau}}_i - l_i M_{i0}(q_i)\ddot{q}_i$$

$$= -l_i\hat{\tau}_i + l_i(C_{i0}\dot{q}_i + G_{i0} + \hat{h}_i(q,\dot{q},\ddot{q}) + \tau_{ci})$$

$$= -l_i(d_i + b_i) + l_i(C_{i0}\dot{q}_i + G_{i0} + \hat{h}_i(q,\dot{q},\ddot{q}) + \tau_{ci})$$

$$= -l_i d_i + l_i(C_{i0}\dot{q}_i + G_{i0} + \hat{h}_i(q,\dot{q},\ddot{q}) + \tau_{ci} - b_i)$$

Improved torque observer is

$$\begin{cases} \dot{d}_i = -l_i d_i + l_i(C_{i0}\dot{q}_i + G_{i0} + \hat{h}_i(q,\dot{q},\ddot{q}) + \tau_{ci} - b_i) \\ \hat{\tau}_i = d_i + b_i \\ b_i = l_i M_{i0}(q_i)\dot{q}_i \end{cases} \tag{19}$$

Under the premise of the observation error is uniformly ultimately bounded in the equation (19), the Jacobian matrix can realize the conversion between the force and torque, and finally get the end contact force of the reconfigurable manipulator.