Adaptive Fuzzy Finite-Time Command Filtered Impedance Control for Robotic Manipulators

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ABSTRACT In order to improve the security and compliance of physical human-robot interaction (pHRI), an adaptive fuzzy impedance control for robotic manipulators based on finite-time command filtered method is proposed in this paper. Firstly, robots usually encounter system uncertainties in practical applications, and the adaptive fuzzy control is introduced to approximate the system uncertainties. Secondly, the finite-time control method is used to improve the interaction performance of the system. Then, the command filtered control technique is used to deal with the “computational complexity” of traditional backstepping. Finally, simulations are conducted to illustrate the effectiveness of the proposed control method in physical human-robot interaction.

INDEX TERMS Physical human-robot interaction (pHRI), adaptive fuzzy control, impedance control, finite-time control, command filtered control.

I. INTRODUCTION

In recent years, robots have been widely applied in social services, such as rehabilitation [1], home service [2], education and entertainment [3]. Physical human-robot interaction has become one of the active research fields in social service robots [4], [5]. It should be concerned that security and compliance should be guaranteed in pHRI. Hence, researchers pay more attention to how to design more effective control strategies to achieve better interaction effects. To regulate the physical interaction between humans and robots, impedance-based controllers have been widely used [6]–[8]. In addition, robots usually encounter system uncertainties in practical applications [9], [10], such as sensor error, and parameters change, which will affect the performance of the robot control if they are not handled properly. Therefore, it is crucial to study the effective impedance control approaches for robots, which ensure the physical interaction performance by dealing with robot system uncertainties.

During the past years, many research results show that fuzzy logic control plays a significant role in estimating the dynamic model of complex nonlinear systems [11], [12], and various impedance control approaches based on the adaptive control [13], [14] and fuzzy logic control [15]–[17] have been proposed for uncertain manipulators. Among these works, an impedance sliding mode control with adaptive fuzzy compensation scheme was proposed in [15] which employing adaptive fuzzy to estimate uncertain model. In [17], an adaptive fuzzy impedance control method where the fuzzy logic system (FLS) was used to approximate unknown nonlinear dynamics was exploited for pHRI. To improve interaction performance in pHRI, finite-time control [18]–[20] has been used in robotic manipulators. In [18], S. Yu introduced finite-time control into the robotic manipulator system, combined with terminal sliding mode technique to achieve a higher precision control performance and converge to the equilibrium in finite time. Up till now, the finite-time impedance control of uncertain manipulators has been seldom studied because it is extremely tough to eliminate the influence of manipulator uncertainty in the design of the finite-time impedance controller. Hence, it is a challenging work how to extend the finite-time impedance control to the uncertain manipulator to ensure the finite-time convergence of the control error.

In another research field, backstepping is one of the most effective control techniques for strict-feedback nonlinear systems, but the repeated derivatives of the virtual control
law in the backstepping control increase the “computational complexity” [21], [22]. For the sake of solving this problem, the dynamic surface control (DSC) was proposed by Swaroop et al. [23], Zhang and Ge [24], Yu et al. [25], but it doesn’t take into account the problem of approximation errors generated by the first-order filters, and the control quality of the system may be affected. Therefore, Farrell et al. proposed command filtered control (CFC) [26]–[28], which solves approximation errors problem by some compensated signals, and reduces the complexity of the controller design. However, how to design the finite-time command filtered impedance control for the robotic manipulator systems is still a problem to be solved.

Based on the observations above, this paper proposes an adaptive fuzzy finite-time command filtered impedance control (AFFTCFIC) method for robotic manipulators to improve interaction performance. Adaptive fuzzy control is used to approximate the uncertain dynamics. The finite-time control was used to improve pHRI performance. CFC technique can deal with the issue of the “computational complexity” in the backstepping design, and overcome approximation errors problem for DSC by designing compensated signals. Lyapunov stability criterion is used for stability analysis. The primary contributions of the proposed control method can be summarized as follows:

- In the face of pHRI system, an AFFTCFIC scheme is proposed for the first time, which can achieve desired tracking performance in finite time. Hence, it expands the application scope for practical pHRI systems.

- Command filtered control technique with compensation signals is adopted to solve the problem of the “computational complexity” in the process of classical backstepping impedance controller design in [17].

- Compared with [15] and [17], the finite-time control can ensure the impedance control of the robot system with higher control accuracy and faster convergence speed. Therefore, it is introduced into the impedance control of the robotic manipulator, which can improve the interaction performance in pHRI system.

Notation: To facilitate the design of the AFFTCFIC. Let $v_\beta^* = \left[v_1^\beta, v_2^\beta, \ldots, v_n^\beta \right]$, $(i = 1, \ldots, n, n \in N^*)$. The Euclidean norm of a vector is denoted by $\|s\|$. The maximum and minimum eigenvalues of the matrix $*$ are denoted by $\lambda_{\text{max}}(*)$ and $\lambda_{\text{min}}(*)$, respectively.

The rest of this study is arranged as follows. The mathematical model and preliminaries are given in Section II. AFFTCFIC controller design and stability analysis are presented in Sections III and IV. Simulink results and conclusions are shown in Sections V and VI.

II. MATHEMATICAL MODEL AND PRELIMINARIES

A. SYSTEM DESCRIPTION

Consider a physical human-robot interaction system, including a P-link manipulator and the force sensor mounted on the end-effector ($P \geq 1$). A P-link manipulator dynamics [29] in Cartesian space is described as

$$D(x)\ddot{x} + C(x, \dot{x})\dot{x} + G(x) = \tau - \tau_e$$

where $x, \dot{x}, \ddot{x} \in \mathbb{R}^n$ are the position, velocity, acceleration vectors at the end-effector of the manipulator in Cartesian space, $D(x)\ddot{x} \in \mathbb{R}^n$ denotes the inertia force vector of the manipulator in Cartesian space, $C(x, \dot{x})\dot{x} \in \mathbb{R}^n$ denotes the Centripetal and Coriolis force vector of the manipulator in Cartesian space, $G(x) \in \mathbb{R}^n$ denotes the gravitational force vector of the manipulator in Cartesian space, $\tau \in \mathbb{R}^n$ denotes the control input vector, $\tau_e \in \mathbb{R}^n$ denotes the vector of constraining force on robotic end-effector in Cartesian space, which is 0 when the robotic manipulator is no contact with human or environment. $n$ denotes the dimension of the operational space.

Property 1 ([30], [31]): The matrix $D(x)$ is symmetric positive definite.

Property 2 ([30], [31]): The matrix $\frac{1}{2}D(x) - C(x, \dot{x})$ is skew-symmetric.

For the convenience, $D$, $C$ and $G$ represent $D(x)$, $C(x, \dot{x})$ and $G(x)$, respectively.

Let $\dot{x} = x$ and $\dot{x} = \dot{x}_1$. Equation (1) becomes

$$\ddot{x}_1 = D^{-1}[\tau - \tau_e - Cx_2 - G].$$

When the manipulator comes into contact with human or environment, an interaction force will be generated based on the user-defined dynamics, the target impedance. The desired impedance dynamics in the workspace [32] is expressed as

$$M_d\ddot{e} + B_d\dot{e} + K_d e = \tau_e,$$

where $e = x_d - x_r$, $x_d$ denotes the commanded trajectory, $x_d$ denotes the desired trajectory, the desired inertia, damping, and stiffness matrices are denoted by $M_d$, $B_d$, and $K_d$ specified by the user, respectively. If the manipulator moves in free space, there has $x_d = x_d$ and $\tau_e = 0$. However, when the manipulator is in contact with the environment, the contact force of the end-effector is defined by the desired impedance dynamics (3). If $x$ tracks $x_r$ precisely, (3) becomes

$$M_d(\ddot{x}_d - \ddot{x}) + B_d(\dot{x}_d - \dot{x}) + K_d(x_d - x) = \tau_e.$$

It should be mentioned that $\tau_e$ can be measured from force sensor on robotic end-effector, $M_d$, $B_d$, $K_d$ and $x_d$ are defined by the user. Therefore, $x_d$ can be calculated from (3).

B. FUZZY LOGIC SYSTEM

An FLS is composed of three parts: 1) the fuzzifier; 2) the fuzzy inference engine for processing fuzzy rules; and 3) the defuzzifier [33]–[35].

Consider $l$ fuzzy IF-THEN rules $R^{(s)}$, $s = 1, \ldots, l$, where $R^{(s)}$ represents the $s$th rule. The fuzzifier maps the input point $x_i$ in the input space $U \subset \mathbb{R}^n$ to a fuzzy set $A_i$ in the input space, and $x = [x_1, x_2, \ldots, x_n]D \in U$ is the input vector of the fuzzy system. Membership functions of linguistic variable $x_i$ for $i = 1, \ldots, n$ are used to represent fuzzy sets. The fuzzy inference engine implements a mapping from fuzzy sets in the
input space to fuzzy sets in the output space \( V \subseteq \mathbb{R}^m \) based on fuzzy rules, and \( y = [y_1, y_2, \ldots, y_m]^T \in V \) is the output vector of the fuzzy system. Finally, the defuzzifier maps fuzzy sets in the output space \( V \) into a crisp output value. The fuzzy logic system is

\[
y_j = \frac{\sum_{s=1}^{l} \left( \prod_{i=1}^{n} \mu_{A_i} \right) y_j^f}{\sum_{s=1}^{l} \left( \prod_{i=1}^{n} \mu_{A_i} \right)}, \quad j = 1, \ldots, m, \tag{4}
\]

where \( \mu_{A_i} = \exp \left[ -\left( x_i - c_{i,i}\sigma_i^2 \right) / \sigma_i^2 \right] \). For the sake of clarity, the fuzzy basis function vector and weight vector are defined as \( \phi(x, c, \sigma) = [\phi_1, \phi_2, \ldots, \phi_l]^T \) and \( \theta_j = [y_1, y_2, \ldots, y_m]^T \), respectively, where \( \sum_{s=1}^{l} \left( \prod_{i=1}^{n} \mu_{A_i} \right) \). \( \sigma = [\sigma_1^T, \sigma_2^T, \ldots, \sigma_n^T]^T \) and \( c = [c_1^T, c_2^T, \ldots, c_n^T]^T \). Hence, (4) can be described as

\[
y_j = \theta_j^T \phi(x, c, \sigma). \tag{5}
\]

FLS can approximate any given continuous function \( f_j(x) \), \( j = 1, 2, \ldots, m \), to arbitrary accuracy on a compact set \( \Omega \). Hence, for any constant \( \delta_j > 0 \), there is a \( \theta_j^T \phi(x) \) in the FLS that makes

\[\sup_{x \in \Omega} |f_j(x) - \theta_j^T \phi(x)| \leq \delta_j \]

where \( \theta_j^T \) is an actual vector, \( \epsilon_j \) is the approximation error, which on page satisfies \( \max_{x \in \Omega} \left\| \epsilon_j \right\| \leq \delta_j \).

**C. PRELIMINARIES**

**Lemma 1 [36]:** For any real numbers \( \lambda_1 > 0, \lambda_2 > 0, 0 < \beta < 1 \), then the finite-time stable Lyapunov condition can be expressed as: \( V(x) \leq -\lambda_1 V(x) - \lambda_2 V^p(x) \). The convergence time by \( T_\beta \leq t_0 + [1/\lambda_1(1 - \beta)] \ln \left( \lambda_1 V_1^{1-\beta}(t_0) + \lambda_2 / \lambda_1 \right) \) to estimate.

**Lemma 2 [37]:** For \( x_i \in \mathbb{R}, i = 1, 2, \ldots, n, 0 < p < 1 \), then

\[
\sum_{i=1}^{n} |x_i|^p \leq \sum_{i=1}^{n} |x_i|^\beta \leq \left( \sum_{i=1}^{n} |x_i| \right)^p
\]

**Lemma 3 [38]:** For real variables \( x \) and \( y \), and given positive constants \( b_1, b_2, b_3 \), the following relation holds:

\[
|x_b^a y_b^a| \leq \frac{b_2}{b_1 + b_2} b_3 \frac{b_1}{b_2} |x_b^a| + b_3 \frac{b_1}{b_2} |y_b^a| + b_3 |b_1| b_2 |b_2| + b_3 |b_1|^2 + b_2^2 |b_2|^2
\]

**Lemma 4 ( [39], [40]):** The Levant differentiator is described as follows:

\[
\begin{align*}
\dot{\phi}_1 &= \xi \quad \dot{\xi} = -R_1 \Delta \text{sign}(\phi_1 - \alpha) + \phi_2, \\
\dot{\phi}_2 &= -R \text{sign}(\phi_1 - \alpha)
\end{align*}
\]

where \( \Delta = \text{diag}(\{\phi_1 - \alpha, \ldots, \phi_m - \alpha\}^2) \). \( \alpha \) is the input signal of the differentiator, \( \phi_1 = x_{1,c} \) and \( \phi_2 = \dot{x}_{1,c} \) are the output signals of the differentiator. Select properly parameters \( R_1 \) and \( R_2 \), the following equations are true when there are no input noises after a transient process of the finite-time.

\[
\phi_1 = \alpha_0, \quad \xi = \dot{a}_0
\]

and the differentiator’s solutions have finite-time stability.

When the differentiator’s input signal is given to be unaffected by noise, that is \( \alpha = \alpha_0 \). Consider the input noise satisfying the inequality \( |\alpha - \alpha_0| \leq \kappa \). Hence, the following inequalities completely dependent on differentiator parameters \( R_1 \) and \( R_2 \) hold in finite time:

\[
\begin{align*}
|\phi_1 - \alpha_0| \leq \theta_1 \kappa = \tilde{\omega}_1 \\
|\xi - \dot{a}_0| \leq \theta_1 \kappa = \tilde{\omega}_2
\end{align*}
\]

where \( \theta_1 \) and \( \tilde{\omega}_1 \) are normal numbers determined by the first-order Levant differentiator design parameters. \( \tilde{\omega}_1 \) and \( \tilde{\omega}_2 \) are normal numbers.

**III. CONTROL DESIGN**

According to the principle of backstepping method, the error variables are defined as follows:

\[
z_i = x_i - x_r, \quad z_2 = x_2 - x_{1,c}\tag{8}
\]

where \( x_{1,c} \) is the first-order Levant differentiator’s output signal when virtual control law \( \alpha \) is the input signal. The error compensation signals are defined as \( \xi_i = z_i - v_i, \) \( i = 1, 2 \) with \( \xi_i(0) = 0 \). The specific structure of virtual control law and the error compensation signals are given in the following design.

**Step 1:** Selecting a Lyaponov function as

\[
V_1 = \frac{1}{2} v_1^T v_1.
\]

Differentiating \( V_1 \) with respect to time yields

\[
\dot{V}_1 = v_1^T \dot{v}_1 + v_1^T (\dot{z}_i - \dot{\xi}_i) = v_1^T (x_2 - \dot{x}_r - \dot{\xi}_1)
\]

Designing virtual control law \( \alpha \) and compensation signal \( \dot{\xi}_1 \) as follows:

\[
\alpha = -K_1 z_1 - \dot{x}_r - S_1 v_1^a, \quad (11)
\]

\[
\dot{\xi}_1 = -K_1 \dot{z}_1 + \dot{\xi}_2 + (x_{1,c} - \alpha) - h_1 \text{sign}(\xi_i), \quad (12)
\]

where the gain matrix \( K_1 = K_1^T > 0, S_1 = S_1^T > 0, \) the parameter \( 0 < \beta < 1, h_1 > 0 \).

Substituting equations (11) and (12) into equation (10) yields

\[
\dot{V}_1 = -v_1^T K_1 v_1 + v_1^T v_2 - v_1^T S_1 v_1^a + h_1 v_1^T \text{sign}(\xi_i)
\]

**Step 2:** Then, selecting the Lyaponov function as

\[
V_2 = V_1 + \frac{1}{2} v_2^T D v_2
\]

and taking its time derivative yields

\[
\dot{V}_2 = \dot{V}_1 + v_2^T \dot{D} v_2 + \frac{1}{2} v_2^T D v_2
\]

\[
= v_2^T (\tau - \tau_e - G - C x_2 + v_1 D (\dot{x}_{1,c} + \dot{\xi}_2)) - v_1^T K_1 v_1
\]

\[
- v_1^T S_1 v_1^a + h_1 v_1^T \text{sign}(\xi_i) + \frac{1}{2} v_2^T \dot{D} v_2.
\]
Since there are uncertainties in $D$, $C$ and $G$, FLSs are used to approximate the uncertainties in $D$, $C$, and $G$. The fuzzy-approximation-based adaptive impedance control will be designed to approach the uncertain dynamics of the robotic manipulator and to adjust the interaction between human and manipulator.

Designing the control law $\tau$ as

$$
\tau = -K_2 z_2 + \tau_2 + \hat{\theta}_D \phi_D (Z_D) \dot{x}_1 + \hat{\theta}_C \phi_C (Z_C) x_1 \dot{c} + \hat{\theta}_G \phi_G (Z_G) - v_1 - S_2 v_2 - K_r \text{sign}(v_2),
$$  
(16)

where the gain matrix $K_2 = K_2^T > 0$, $S_2 = S_2^T > 0$, $K_r = \text{diag} [k_{ri}i]$ > 0, $\hat{\theta}_D$, $\hat{\theta}_C$ and $\hat{\theta}_G$ are the estimate weight matrices, $\theta_D^*$, $\theta_C^*$ and $\theta_G^*$ are the actual weight matrices, $\dot{\theta}_D = \theta_D - \theta_D^*$, $\dot{\theta}_C = \theta_C - \theta_C^*$ and $\dot{\theta}_G = \theta_G - \theta_G^*$ are the weight error matrices, $Z_D = [x_1^T, x_1^T, \ldots, x_1^T]^T$, $Z_C = [x_1^T, x_1^T, \ldots, x_1^T]^T$ and $Z_G = [x_1^T, x_1^T, \ldots, x_1^T]^T$ are FLS inputs, respectively.

The updating laws are designed as

$$
\dot{\hat{\theta}}_D = -\Gamma_{DK} \left( \sigma_{DK} \hat{\theta}_D + \phi_D (Z_D) \dot{x}_1 v_2 \right),
$$  
(17)

$$
\dot{\hat{\theta}}_C = -\Gamma_{CK} \left( \sigma_{CK} \hat{\theta}_C + \phi_C (Z_C) x_1 v_2 \right),
$$  
(18)

$$
\dot{\hat{\theta}}_G = -\Gamma_{GK} \left( \sigma_{GK} \hat{\theta}_G + \phi_G (Z_G) v_2 \right),
$$  
(19)

where $\Gamma_{DK} > 0$, $\Gamma_{CK} > 0$, $\Gamma_{GK} > 0$, and $\sigma_{DK}$, $\sigma_{CK}$, $\sigma_{GK}$ are positive constants for improving the robustness. $\hat{\theta}_D^T \phi_D (Z_D)$ is an estimation matrix of $\theta_D^T \phi_D (Z_D)$, $\hat{\theta}_C^T \phi_C (Z_C)$ is an estimation matrix of $\theta_C^T \phi_C (Z_C)$ and $\hat{\theta}_G^T \phi_G (Z_G)$ is an estimation matrix of $\theta_G^T \phi_G (Z_G)$.

$$
\theta_D^T \phi_D (Z_D) = D + \epsilon_D,
$$  
(20)

$$
\theta_C^T \phi_C (Z_C) = C + \epsilon_C,
$$  
(21)

$$
\theta_G^T \phi_G (Z_G) = G + \epsilon_G.
$$  
(22)

where $\epsilon_D$, $\epsilon_C$, and $\epsilon_G$ are small approximation errors.

For the convenience of derivation, choosing $\dot{\xi}_2 = 0$.

Substituting the control law (16) and equations (20)-(22) into (15) and Property 2 is used, there is

$$
\dot{V}_2 = -v_1^T K_1 v_1 - v_1^T S_1 v_1^\beta - v_1^T K_2 v_2 - v_1^T S_2 v_2^\beta
+ v_2^T \hat{\theta}_D^T \phi_D (Z_D) \dot{x}_1 + v_2^T \hat{\theta}_C^T \phi_C (Z_C) x_1 + v_2^T \hat{\theta}_G^T \phi_G (Z_G) + v_2^T (E_r - K_r \text{sign}(v_2))
+ h_1 v_1^T \text{sign}(\xi_1),
$$  
(23)

where $E_r = \epsilon_D x_1 + \epsilon_C x_1 + \epsilon_G$, $E_{ri}$, $i = 1, \ldots, n$ is ith element of a vector, there has $E_r = [E_{r1}, \ldots, E_{rn}]$. \textbf{IV. STABILITY ANALYSIS}

For the stability analysis, the Lyapunov function is selected as

$$
V = V_2 + \frac{1}{2} \sum_{k=1}^{n} \sigma_{DK} \Gamma_{DK}^{-1} \hat{\theta}_D + \frac{1}{2} \sum_{k=1}^{n} \sigma_{CK} \Gamma_{CK}^{-1} \hat{\theta}_C + \frac{1}{2} \sum_{k=1}^{n} \sigma_{GK} \Gamma_{GK}^{-1} \hat{\theta}_G,
$$  
(24)

Substituting (17)-(19) and (23) into the time derivative of (24) yields

$$
\dot{V} = -v_1^T K_1 v_1 - v_1^T S_1 v_1^\beta - v_1^T K_2 v_2 - v_1^T S_2 v_2^\beta
+ v_2^T \hat{\theta}_D^T \phi_D (Z_D) \dot{x}_1 + v_2^T \hat{\theta}_C^T \phi_C (Z_C) x_1 + v_2^T \hat{\theta}_G^T \phi_G (Z_G) + v_2^T (E_r - K_r \text{sign}(v_2))
- \sum_{k=1}^{n} \sigma_{DK} \hat{\theta}_D^{T} \dot{\hat{\theta}}_D
- \sum_{k=1}^{n} \sigma_{CK} \hat{\theta}_C^{T} \dot{\hat{\theta}}_C
- \sum_{k=1}^{n} \sigma_{GK} \hat{\theta}_G^{T} \dot{\hat{\theta}}_G
+ h_1 v_1^T \text{sign}(\xi_1),
$$  
(25)

nothing that

$$
v_2^T \hat{\theta}_D^T \phi_D (Z_D) \dot{x}_1 = \sum_{k=1}^{n} \sigma_{DK} \hat{\theta}_D^{T} \dot{\hat{\theta}}_D
$$

$$
v_2^T \hat{\theta}_C^T \phi_C (Z_C) x_1 = \sum_{k=1}^{n} \sigma_{CK} \hat{\theta}_C^{T} \dot{\hat{\theta}}_C
$$

$$
v_2^T \hat{\theta}_G^T \phi_G (Z_G) = \sum_{k=1}^{n} \sigma_{GK} \hat{\theta}_G^{T} \dot{\hat{\theta}}_G
$$

Based on Young’s inequality, there holds

$$
-\hat{\theta}_D^{T} \dot{\hat{\theta}}_D \leq -\frac{1}{2} \sigma_{DK} \hat{\theta}_D^{T} \hat{\theta}_D + \frac{1}{2} \sigma_{DK} \hat{\theta}_D^{T} \hat{\theta}_D,
$$

$$
-\hat{\theta}_C^{T} \dot{\hat{\theta}}_C \leq -\frac{1}{2} \sigma_{CK} \hat{\theta}_C^{T} \hat{\theta}_C + \frac{1}{2} \sigma_{CK} \hat{\theta}_C^{T} \hat{\theta}_C,
$$

$$
-\hat{\theta}_G^{T} \dot{\hat{\theta}}_G \leq -\frac{1}{2} \sigma_{GK} \hat{\theta}_G^{T} \hat{\theta}_G + \frac{1}{2} \sigma_{GK} \hat{\theta}_G^{T} \hat{\theta}_G,
$$

$$
h_1 v_1^T \text{sign}(\xi_1) \leq \frac{h_1}{2} v_1^T v_1 + \frac{n h_1}{2}.
$$

(32)

Substituting (26)-(32) into (25) with $K_{ri} \geq \|E_{ri}\|$ yields

$$
\dot{V} \leq -v_1^T \left( K_1 - \frac{h_1}{2} \right) v_1 - v_1^T S_1 v_1^\beta - v_1^T K_2 v_2 - \frac{1}{2} \sum_{k=1}^{n} \sigma_{DK} \hat{\theta}_D^{T} \hat{\theta}_D
- \frac{1}{2} \sum_{k=1}^{n} \sigma_{CK} \hat{\theta}_C^{T} \hat{\theta}_C
- \frac{1}{2} \sum_{k=1}^{n} \sigma_{GK} \hat{\theta}_G^{T} \hat{\theta}_G
+ \frac{1}{2} \sum_{k=1}^{n} \sigma_{DK} \hat{\theta}_D^{T} \hat{\theta}_D
+ \frac{1}{2} \sum_{k=1}^{n} \sigma_{CK} \hat{\theta}_C^{T} \hat{\theta}_C
+ \frac{1}{2} \sum_{k=1}^{n} \sigma_{GK} \hat{\theta}_G^{T} \hat{\theta}_G
+ \frac{n h_1}{2}.
$$

(33)

Applying Lemma 3 to the terms $\sum_{k=1}^{n} \sigma_{DK} \hat{\theta}_D^{T} \hat{\theta}_D$ with $y = 1$, and
\[ b_1 = \frac{\beta + 1}{2}, \quad b_2 = 1 - \frac{\beta + 1}{2}, \quad b_3 = \left(1 - \frac{\beta}{2}\right)\frac{1}{\sqrt{\pi}}, \] there holds

\[ \left(\sum_{k=1}^{n} \frac{\sigma_{Dk} \bar{T}_{Dk} \bar{D}_{pk}}{4}\right)^{\frac{\beta + 1}{2}} \leq \frac{1}{4} \sum_{k=1}^{n} \sigma_{Dk} \bar{T}_{Dk} \bar{D}_{pk} + b_1 b_3, \] (34)

\[ \left(\sum_{k=1}^{n} \frac{\sigma_{Ck} \bar{T}_{Ck} \bar{D}_{ck}}{4}\right)^{\frac{\beta + 1}{2}} \leq \frac{1}{4} \sum_{k=1}^{n} \sigma_{Ck} \bar{T}_{Ck} \bar{D}_{ck} + b_1 b_3, \] (35)

\[ \left(\sum_{k=1}^{n} \frac{\sigma_{Gk} \bar{T}_{Gk} \bar{D}_{gk}}{4}\right)^{\frac{\beta + 1}{2}} \leq \frac{1}{4} \sum_{k=1}^{n} \sigma_{Gk} \bar{T}_{Gk} \bar{D}_{gk} + b_1 b_3. \] (36)

According to Lemma 2 and \( v_j = [v_{j,1}, v_{j,2}, \ldots, v_{j,n}]^T \), there holds

\[ v_j^T \dot{v}_j = [v_{j,1}, v_{j,2}, \ldots, v_{j,n}] [v_{j,1}, v_{j,2}, \ldots, v_{j,n}]^T \]

\[ = v_{j,1}^{\beta + 1} + v_{j,2}^{\beta + 1} + \cdots + v_{j,n}^{\beta + 1} \geq \left(\sum_{j=1}^{n} v_j^T v_j\right)^{\frac{\beta + 1}{2}}. \] (37)

Substituting (34)-(37) into (33) yields

\[ \dot{V} \leq -v_1^T \left(K_1 - \frac{h_1}{2}\right) v_1 - v_1^T S_1 v_1^\beta - v_2^T S_2 v_2^\beta + \frac{1}{4} \sum_{k=1}^{n} \sigma_{Dk} \bar{T}_{Dk} \bar{D}_{pk} \]

\[ - \frac{1}{4} \sum_{k=1}^{n} \sigma_{Ck} \bar{T}_{Ck} \bar{D}_{ck} - \frac{1}{4} \sum_{k=1}^{n} \sigma_{Gk} \bar{T}_{Gk} \bar{D}_{gk} \]

\[ \leq -a \dot{V} - b V^{\frac{\beta + 1}{2}} + c, \] (38)

where \( K_1 - \frac{h_1}{2} > 0, \quad \frac{1}{2} \leq \frac{\beta + 1}{2} \leq 1, \)

\[ a = \min \left\{ \lambda_{\min}(2K_1 - h_1), \min_{k=1,\ldots,n} \frac{\sigma_{Dk}}{2\lambda_{\max}(\Gamma_{Dk}^{-1})}, \right. \]

\[ \left. \frac{\lambda_{\min}(2K_2)}{\lambda_{\max}(D)}, \min_{k=1,\ldots,n} \left\{ \frac{\sigma_{Ck}}{2\lambda_{\max}(\Gamma_{Ck}^{-1})}, \frac{\sigma_{Gk}}{2\lambda_{\max}(\Gamma_{Gk}^{-1})} \right\} \right\}, \] (39)

\[ b = \min \left\{ \min_{k=1,\ldots,n} \left(\frac{\sigma_{Dk}}{2\lambda_{\max}(\Gamma_{Dk}^{-1})}\right) \frac{\beta + 1}{2}, \min_{k=1,\ldots,n} \left(\frac{\sigma_{Ck}}{2\lambda_{\max}(\Gamma_{Ck}^{-1})}\right) \frac{\beta + 1}{2}, \min_{k=1,\ldots,n} \left(\frac{\sigma_{Gk}}{2\lambda_{\max}(\Gamma_{Gk}^{-1})}\right) \frac{\beta + 1}{2} \right\}, \]

\[ c = \frac{1}{2} \sum_{k=1}^{n} \sigma_{Dk} \bar{T}_{Dk} \bar{D}_{pk} + \frac{1}{2} \sum_{k=1}^{n} \sigma_{Ck} \bar{T}_{Ck} \bar{D}_{ck} \]

\[ + \frac{1}{2} \sum_{k=1}^{n} \sigma_{Gk} \bar{T}_{Gk} \bar{D}_{gk} + b_1 b_3 + \frac{nh_1}{2}. \] (41)

Rewrite (41) as follows

\[ \dot{V} \leq -a \dot{V} - b V^{\frac{\beta + 1}{2}} + c. \] (42)

From (42), selecting parameters can obtain \( a > c V^{\frac{\beta + 1}{2}} \), \( b > \frac{c}{2V^{\frac{\beta + 1}{2}}} \). By Lemma 1, \( v_j(j = 1, 2) \) will be within the finite-time \( T_1 \) converge to the domain \( \|v_j\| \leq \max \left\{ \sqrt{c/\alpha}, \sqrt{2(c/2b)^{\frac{\beta + 1}{2}}} \right\} \).

Remark 1: Control parameters determine the radius of the tracking error domain, that is, the smallest radius of the tracking error domain can be ensured by the larger parameters \( \lambda_{\max}(K_i) \) and \( \lambda_{\max}(S_i) \).

Remark 2: In the control law, the \( K_r \) is chosen as \( K_r \gg \|E_{ri}\| \). For stability, \( K_r \) is chosen to be properly large. This is not very ideal due to the introduction of the chattering. Therefore, the control parameter \( K_r \) can be changed as \( K_r = k_D \tilde{x}_{1,c} + k_C X_{1,c} + k_G \), where \( k_D \gg \|E_D\|, k_C \gg \|E_{ci}\|, \)

\( k_G \gg \|e_G\| \).

Theorem 1: Consider manipulator dynamics (1) with Property 1, 2 and impedance dynamics (3). If the finite-time command filter and the error compensation mechanism are chosen as (7), (12), and the adaptive FLS control law (16) with updating laws (17)-(19) are chosen, the tracking error \( z_1 \) converges to a small enough region with the radius \( \max \left\{ \sqrt{c/\alpha}, \sqrt{2(c/2b)^{\frac{\beta + 1}{2}}} \right\} \) in finite time \( T \geq \max \left\{ T_1, T_2 \right\} \).

The proof of Theorem 1 is given in the Appendix.

Remark 3: In the proof of Theorem 1, the result \( |X_{1,c} - \bar{a}| \leq \tilde{w}_1 \) from Lemma 4 will be used. Note that if the \( \alpha \) of the finite-time command filter (7) is not influenced by the noise, there has \( \tilde{w}_1 = 0 \). Therefore, the conclusion of Theorem 1 can be obtained when the noise is bounded.

Remark 4: Note that the manipulator is a highly nonlinear system. The finite-time convergence speed in the nonlinear system.
the proposed method and the robotic manipulator system of
is considered, simulations of pHRIs verify the validity of
manipulator on a vertical plane, which is shown in Fig.3,
In this section, a 2-degrees of freedom (2-DOF) robotic
variables in the robot system can be
infinite time, and that all signals in the robot system can be
variable ing mode control can only deal with the matched unknown
convergence capability of the unknown manipulator system
the PID control. Although the excellent robustness and fast
tracking performance cannot be guaranteed by the traditional PID control.
When the nonlinear system contains unknown dynamics,
the parameters of the 2-DOF manipulator are shown as
the total length of link 1 and link 2 are 1
and Coriolis matrix $\mathbf{C}_c$ are respectively the position of the axis $X$ and $Y$ on the
end-effector. $\mathbf{q}$ is the joint angle position, $m_i$ and $l_i$ are respectively the mass and length of link $i$, $l_{ci}$ is the distance from joint $i - 1$ of the robotic manipulator to the centroid of the link $i$, $I_i$ is the moment of inertia of link $i$ through the centroid of link $i$, $(i = 1, 2)$ based on the axis of the page.
The inertia matrix of 2-DOF manipulator $\mathbf{D}_s$, Centripetal and Coriolis matrix $\mathbf{C}_s$, gravity force vector $\mathbf{G}_s$ are given as follows:

$$\mathbf{D}_s = \begin{bmatrix} m_1 l_1^2 + m_2 l_1^2 + l_1^2 + 2l_1 l_2 \cos q_2 + l_1 + l_2 \\ m_1 l_2^2 + m_2 l_2 \cos q_2 + l_2 \\ m_2 \left(l_2^2 + l_1 l_2 \cos q_2 + l_1 \right) \\ m_2 \left(l_2^2 + l_1 l_2 \cos q_2 + l_1 \right) \end{bmatrix}$$

$$\mathbf{C}_s = \begin{bmatrix} -m_2 l_1 l_2 \sin q_2 \\ -m_2 l_1 l_2 \sin q_2 \\ m_1 l_2 \cos q_1 + m_2 l_2 g \cos \left(q_1 + q_2 \right) \\ m_1 l_2 \cos q_1 + m_2 l_2 \cos q_1 + q_2 \end{bmatrix}$$

$$\mathbf{G}_s = \begin{bmatrix} \left(m_1 l_2 + m_2 l_1 \right) g \cos q_1 + m_2 l_2 g \cos q_1 + q_2 \\ \left(m_1 l_2 + m_2 l_1 \right) g \cos q_1 + m_2 l_2 g \cos q_1 + q_2 \end{bmatrix}$$

The Jacobian matrix of 2-DOF robotic manipulator is shown as follows:

$$\mathbf{J} = \begin{bmatrix} -\left(l_1 \sin q_1 + l_2 \sin \left(q_1 + q_2 \right) \right) \\ -l_2 \sin \left(q_1 + q_2 \right) \\ l_1 \cos q_1 + l_2 \cos \left(q_1 + q_2 \right) \\ l_2 \cos q_1 + l_2 \cos q_1 + q_2 \end{bmatrix}$$

Some formulas for robotic system are $\mathbf{D} = \mathbf{J}^T \mathbf{D}_s \mathbf{J}^{-1}$, $\mathbf{C} = \mathbf{J}^T \left(\mathbf{C}_s - \mathbf{D}_s \mathbf{J}^{-1} \mathbf{C}_s \right) \mathbf{J}^{-1}$, and $\mathbf{G} = \mathbf{J}^T \mathbf{G}_s$.
The parameters of the 2-DOF manipulator are shown as the length of link 1 and link 2 are 1.0m, the mass of link 1 and link 2 are 1.00kg, the moment of inertia of link 1 and link 2 are 0.25kg $\cdot$ m$^2$. The initial parameters of the robotic manipulator are $x_{11}(0) = 0.4$, $x_{12}(0) = 1$m, $x_{11}(0) = x_{12}(0) = 0$, $q_1(0) = \frac{\pi}{4}$, $q_2(0) = -\frac{\pi}{4}$, the desired trajectory of the 2-DOF robotic manipulator is shown as
The manipulated end-effector moves along the solid wall when it makes touch with the wall, and the obstacle wall is located as $x_0 = 0.8m$.

The target impedance of the 2-DOF robotic manipulator is selected as $M_d = \text{diag}[1.0, 1.0], B_d = \text{diag}[15.0, 15.0], K_d = \text{diag}[60.0, 60.0]$. The updating law parameters are $\Gamma_{Dk} = \Gamma_{Gk} = \Gamma_{Gk} = \text{diag}[0.01, 0.01]$.

In this part, the PD control method, the adaptive fuzzy impedance control (AFIC) method in [17] and the proposed AFFTCFIC method in this paper are compared. The robotic manipulator system control parameters are chosen as follows:

A). For PD method of the 2-DOF robotic manipulator, the control law is given as $\tau = -K_1z_1 - K_2z_2$ and control parameters are chosen as $K_1 = \text{diag}[800, 800], K_2 = \text{diag}[200, 200]$;

B). For AFIC method of the 2-DOF robotic manipulator in [17], control parameters are given as $K_1 = \text{diag}[6, 6], K_2 = \text{diag}[8, 8]$;

C). For AFFTCFIC method of the 2-DOF robotic manipulator, control the control parameters are given as $K_1 = \text{diag}[6, 6], K_2 = \text{diag}[8, 8], S_1 = \text{diag}[2, 2], S_2 = \text{diag}[2, 2], \gamma = 0.6, h_1 = 1, R_1 = 20, R_2 = 0.6$.

The simulation results are described in Figs.4-8. Among them, Fig.4(a) and Fig.4(b) show the position tracking curves of the manipulator end-effector on the X-axis and Y-axis under three schemes. Fig.5 shows the position tracking error curves of the manipulator end-effector on the X-axis and Y-axis under three schemes. Indicated from Fig.4 to Fig.5, it can be seen that the tracking performances are better under the proposed control method whether the manipulator contact with the wall or not, and the proposed AFFTCFIC scheme.

$x_d = [0.7 - 0.2 \cos (t), 0.7 + 0.2 \sin (t)]^T$, where $t \in [0, 10]$. The manipulator end-effector moves along the solid wall when it makes touch with the wall, and the obstacle wall is located as $x_0 = 0.8m$. The manipulator end-effector makes touch with the wall, and the obstacle wall is located as $x_0 = 0.8m$. The target impedance of the 2-DOF robotic manipulator is selected as $M_d = \text{diag}[1.0, 1.0], B_d = \text{diag}[15.0, 15.0], K_d = \text{diag}[60.0, 60.0]$. The updating law parameters are $\Gamma_{Dk} = \Gamma_{Gk} = \Gamma_{Gk} = \text{diag}[0.01, 0.01]$.

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C). For AFFTCFIC method of the 2-DOF robotic manipulator, control the control parameters are given as $K_1 = \text{diag}[6, 6], K_2 = \text{diag}[8, 8], S_1 = \text{diag}[2, 2], S_2 = \text{diag}[2, 2], \gamma = 0.6, h_1 = 1, R_1 = 20, R_2 = 0.6$.
has better control accuracy and faster convergence speed than the AFIC algorithm in [17] and PD algorithm. Figs.6 shows contact forces from the wall on X-axis. When the manipulator contacts with the solid wall, it can be seen that the desired impedance model can be obtained more smoothly and quickly under the AFFTCFIC method and PD control has a relatively large collision force in Fig.6. Fig.7 shows the control inputs are in proper bounds, but the PD control input is relatively large, which is not conducive to practical application. Fig.8 shows that the filtered signal \( x_{1,c} \) has an excellent tracking approximation to the virtual signal \( \alpha \).

VI. CONCLUSION

In this paper, the adaptive fuzzy impedance controller that combines the finite-time control and the CFC technique has been proposed to improve the security and compliance of pHRI. The manipulator tracking quality has been improved by the finite-time control technique. Simultaneously, the combination of the CFC technique and the backstepping can solve the “computational complexity” issue in the backstepping controller design. Through the Lyapunov stability analysis and simulations, the validity of the proposed method is proven. Our future research is to design a novel finite-time state constraint control scheme of robotic manipulators, which can ensure that the manipulator moves in a finite space and achieves the desired performance in finite time.

APPENDIX

Proof of the Theorem 1

Proof: Now the following Lyapunov function is selected.

\[
\tilde{V} = \frac{1}{2} \xi_1^T \xi_1.
\]  

(43)

The differential of (43), with respect to time, is

\[
\dot{\tilde{V}} = -\xi_1^T K_1 \xi_1 + \xi_1^T \left( x_{1,c} - \alpha \right) - h_1 \xi_1^T \text{sign}(\xi_1).
\]  

(44)

Based on Lemma 2 and Young’s inequality, there holds

\[
h_1 \xi_1^T \text{sign}(\xi_1) \geq h_1 \left( \xi_1^T \xi_1 \right)^{\frac{1}{2}},
\]  

(45)

let \( d = (x_{1,c} - \alpha) \), there holds

\[
\xi_1^T d \leq \frac{1}{2} \xi_1^T \xi_1 + \frac{1}{2} d^T d.
\]  

(46)

According to Lemma 4, there is \( |x_{1,c} - \alpha| \leq \tilde{w}_1 \) in finite time \( T_2 \), and substituting (45) and (46) into (44). For \( t > T_2 \), there holds

\[
\dot{\tilde{V}} \leq -\xi_1^T \left( K_1 - \frac{1}{2} I \right) \xi_1 - h_1 \left( \xi_1^T \xi_1 \right)^{\frac{1}{2}} + \frac{1}{2} \tilde{w}_1^2
\]

\[
\leq -a_0 \tilde{V} - b_0 \tilde{V}^{\frac{1}{2}} + c_0.
\]  

(47)

where \( K_1 - \frac{1}{2} I > 0 \),

\[
a_0 = 2 \lambda_{\text{min}} \left( K_1 - \frac{1}{2} I \right), \ b_0 = h_1 * 2^2, \ c_0 = \frac{1}{2} \tilde{w}_1^2.
\]

Rewrite (47) as follows

\[
\dot{\tilde{V}} \leq - \left( a_0 - \frac{c_0}{2\tilde{V}} \right) \tilde{V} - \left( b_0 - \frac{c_0}{2\tilde{V}^{\frac{1}{2}}} \right) \tilde{V}^{\frac{1}{2}}.
\]  

(48)

From (48), selecting parameters can obtain \( a_0 - \frac{c_0}{2\tilde{V}} > 0, b_0 - \frac{c_0}{2\tilde{V}^{\frac{1}{2}}} > 0 \). By Lemma 1, \( \xi_1 \) can converge to the domain

\[
||\xi_1|| \leq \max \left\{ \sqrt{c_0/a_0}, \sqrt{2(c_0/2b_0)^{\frac{1}{2}}} \right\} \text{ in finite-time } T_2.
\]

Since \( z_1 = v_1 + \xi_1 \), when \( T \geq \max \{ T_1, T_2 \} \), there can obtain

\[
||z_1|| \leq ||v_1|| + ||\xi_1|| \leq \max \left\{ \sqrt{c_0/a_0}, \sqrt{2(c_0/2b_0)^{\frac{1}{2}}} \right\} + \max \left\{ \sqrt{c_0/a_0}, \sqrt{2(c_0/2b_0)^{\frac{1}{2}}} \right\} = \tilde{w}_1.
\]

The proof is completed. □

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