Dual Loop Compliant Control Based on Human Prediction for Physical Human-Robot Interaction

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Abstract: In physical human-robot interaction (HRI), human partner’s operating force and the performance of the HRI process are the two main criterions. Lower operating force and higher tracking accuracy are demanded during physical HRI. In order to achieve such two goals, we propose a dual loop force assist framework for HRI. In this framework, it includes an outer force loop and an inner position loop. In the outer loop, a model reference adaptive control (MRAC) based compensation method is proposed to assist a human operator to interact with robot. The compensation works as an assist force to minimize the error between human desired position and a robot actual position. Besides, a Sparse Bayesian learning (SBL) based human intention predictor is also proposed to predict the future human desired position, thus the MRAC based compensation can work on-line. For the inner loop, the compensated force is used as the input of prescribed impedance, which gives compliance to the robot. Then, the Cartesian drive torque for a n-DOF robot manipulator has been analyzed and a Proportional + Derivative (PD) based controller with gravity compensation is adopted to generate the drive torque. So that the robot can track the output of prescribed impedance accurately. The effectiveness of the proposed framework is verified by simulation study.

Keywords: Human-robot interaction, Compliant control, Dual loop, Human prediction, Impedance

1. INTRODUCTION

In terms of human-robot-interaction (HRI), human and robot have been taken into consideration for tasks, especially complex tasks. To regulate dynamic behaviors between human operator and robot safely, it is of great significance to adopt a proper strategy to achieve such objective. There are mainly two methods to regulate the dynamic relationship, namely Hybrid Position and Force Control and Impedance Control [14].

Nowadays, impedance control has been successfully implemented to many robot compliant applications [15]. Impedance control is firstly proposed by N. Hogan [4] in 1984. He also proves the safety and stability of implementing impedance control to deal with the interaction between robot and environment in his further research. Lasky proposed a force tracking impedance control system in 1991 [6], the simulation results reveal that impedance controller can make robot manipulator track both position and force excellently. Impedance control is also applied to contouring control with constraint in high-speed machining [1]. Researchers are trying to apply impedance control to HRI tasks for decades [2, 5, 8, 9, 11, 17]. In order to make robots work together with human operators compliantly, many frameworks and strategies have been proposed for HRI.

Variable impedance control is the most widely used strategy for compliant collaboration. Ikeura firstly proposed the concept of variable impedance control for HRI [5], the cooperation between two humans were investigated in this paper. The experiments showed that robot can have best performance during cooperation if it modify its impedance characteristics as humans. Tsumugiwa presented a novel variable impedance control method for HRI in 2002 [17], it tunes damping on-line based on the estimation of the stiffness of human arm. A novel variable impedance strategy for redundant robots is proposed by Ficuciello et al. [2]. In this work, the impedance parameters are modulated according to the velocity of robot end effector. Besides, the stability region for impedance parameters are investigated and en-

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{fig1.png}
\caption{General view of proposed HRI framework}
\end{figure}
larged in this work. The stability during HRI is theoretically analyzed in the researches of Muller et al. [11], and then a variable impedance controller and a stability observer are proposed to enhance the performance of HRI.

According to [3], the variable impedance method has the weakness of time-delay during HRI task, which will have an effect on the HRI performance. Therefore we propose a novel HRI framework in this paper to avoid such situation. The overall scheme is shown in 1. The main contributions of the proposed HRI framework are as follows. First, the proposed HRI framework can quantitatively generate an appropriate compensation for HRI, which can eliminate the time-delay in trajectory tracking. Second, the proposed SBL based human intention predictor can predict human desired position accurately. Third, the proposed method can reduce the force that human operator exerted on robot manipulator, thus better performance and more comfort can be achieved during HRI.

2. INNER POSITION LOOP ANALYSIS AND DESIGN

The dynamic model of a robot arm is usually expressed in joint space while impedance equation is formulated in Cartesian space, thus it is necessary to transform dynamic equation into Cartesian space [3]. Considering a robot manipulator with degree of freedom, the dynamic model can be expressed as a second order nonlinear differential function:

\[ B(q)\ddot{q} + C(q, \dot{q})\dot{q} + g(q) = \tau + J^T(q)f_{\text{ext}}, \]

where \( B(q) \in \mathbb{R}^{n \times n} \) is time-varying symmetric positive definite matrix, it is known as the inertia matrix of the robot manipulator. \( q \in \mathbb{R}^n \) represents the joint position of robot manipulator. \( C(q, \dot{q}) \in \mathbb{R}^{n \times n} \) is a matrix, which stands for Coriolis and centrifugal torques. \( g(q) \in \mathbb{R}^n \) is the gravitational force vector. \( J(q) \in \mathbb{R}^{n \times n} \) is known as the geometric Jacobian matrix. \( \tau \), and \( f_{\text{ext}} \in \mathbb{R}^{n \times 1} \) are joint drive torque vector and external force, respectively. Taking the first and second order derivatives of the robot kinematics, the results are:

\[ \dot{p}_a = J(q)\dot{q} \]
\[ \ddot{p}_a = J(q)\ddot{q} + J(q)\dot{q}, \]

where \( p_a \in \mathbb{R}^{n \times 1} \) is the actual position of robot manipulator in Cartesian space. Substituting (2) into (1) yields the Cartesian drive torque expression:

\[ \tau^* = B^*(q)\ddot{p}_a + C^*(q, \dot{q})\dot{p}_a + g^*(q) - f_{\text{ext}}, \]

with

\[ g^*(q) = J^*(q)g(q), \quad \tau^* = J^{-T}(q)\tau \]
\[ B^*(q) = J^{-T}(q)B(q)J^{-1}(q) \]
\[ C^*(q, \dot{q}) = J^{-T}(C - B\dot{J}J^{-1})J^{-1}. \]

Thus the design of Cartesian drive torque has been accomplished. While due to the matrices \( B(q), C(q, \dot{q}) \) are usually unknown and it is difficult to measure accurately, thus in this paper we adopt a PD controller with on-line gravity compensation to deal with such problem. The drive torque can be selected as follows:

\[ \tau^* = K_p\delta + K_d\dot{\delta} + \ddot{g}^*(q) - \ddot{f}_{\text{ext}}, \]

where \( K_p, K_d \in \mathbb{R}^n \) are positive proportional and derivative parameters, respectively. \( \delta = p_a - p_a \) is the error between compliant position of robot manipulator and actual Cartesian position. Notice that compliant position \( p_a \) is generated by the impedance controller which has been introduced in the previous section. \( \ddot{g}^*(q), \ddot{f}_{\text{ext}} \in \mathbb{R}^{n \times 1} \) represent the estimated gravity compensation using [10] method and the measured external force.

Accordingly, by substituting (5) into (3) we have:

\[ K_p\delta + K_d\dot{\delta} + B^*(q)\ddot{p}_a + C^*(q, \dot{q})\dot{p}_a + (\ddot{g}^*(q) - g^*(q)) + (f_{\text{ext}} - f_{\text{ext}}) = 0. \]

Supposing that the measurement of external force and estimation of gravity are accurate, i.e. \( \ddot{g}^*(q) - g^*(q) = 0, f_{\text{ext}} - f_{\text{ext}} = 0 \). And supposing desired position is constant, thus we have \( \ddot{p}_a = 0, \dot{\delta} = 0 \).

(6) can be reformulated as follows:

\[ B^*(q)\ddot{p}_a + C^*(q, \dot{q})\dot{p}_a + K_p\delta = -K_d\dot{\delta}. \]

Theorem 1: Consider the PD control loop, there exists a choice of gain \( K_p, K_d \) that makes the origin of the system (6) asymptotically stable.

Proof: Select a Lyapunov candidate function as:

\[ V = \frac{1}{2}\delta^T B^*\delta + \frac{1}{2}\delta^T K_p\delta > 0. \]

Noting that there is a well-known property of robot dynamic that \( B^*-2C^* \) is a skew-symmetric matrix. Take differentiating of (8) we have:

\[ \dot{V} = \dot{\delta}^T B^*\dot{\delta} + \frac{1}{2}\delta^T B^*\dot{\delta} + \delta^T K_p\dot{\delta} \]
\[ = \delta^T(B^*\dot{\delta} + C^*\dot{\delta} + K_p\delta) \]
\[ = -\delta^T K_d\delta \leq 0. \]

Thus the stability of the PD based controller has been proved.

3. OUTER FORCE LOOP DESIGN

3.1. MRAC-Based Force Compensation

The diagram of outer loop force compensation is shown in Fig. 2. It includes a MRAC based force assist compensation and a SBL based human intention predictor. In this section, the design of MRAC based force assist compensation is illustrated. The purpose of outer-loop compensation is to generate an force to
assist human operator interacting with robot manipulator, thus the operator can drag the robot using less force and the robot can track human desired position better. The human arm muscle has similar characteristics with spring-damper system [12], thus taking mass, damping and stiffness into consideration, human arm model can be established as follow:

\[ M_H \ddot{\mathbf{p}} + D_H \dot{\mathbf{p}} + K_H (\mathbf{p}_d - \mathbf{p}) = \mathbf{f}_H, \]  

(10)

where \( M_H, D_H \) and \( K_H \) are \( n \times n \) mass, damping and stiffness matrices of human arm respectively. \( \mathbf{p}_d, \mathbf{p} \in \mathbb{R}^{n \times 1} \) and they represent human desired position and actual position of robot end effector, respectively. \( \mathbf{f}_H \in \mathbb{R}^{n \times 1} \), it stands for the force exerted on human arm. According to the previous researches [3, 12], since human interaction process does not have influence on mass parameters, here we consider only damping and stiffness in this work as follows:

\[ D_H \ddot{\mathbf{p}} + K_H (\mathbf{p}_d - \mathbf{p}) = \mathbf{f}_H. \]  

(11)

As introduced in the previous section, in order to make robot follow human operator behavior compliantly, impedance control is adopted and the formulation is shown as follows:

\[ M \ddot{\mathbf{p}}_c + D \dot{\mathbf{p}}_c = \mathbf{f}, \]  

(12)

where \( M, D \in \mathbb{R}^{n \times n} \) and represent target mass matrix and target damping matrix respectively. \( \mathbf{p}_c \in \mathbb{R}^{n \times 1} \) is the compliant position generated by the impedance model. \( \mathbf{f} \in \mathbb{R}^{n \times 1} \), it stands for the force exerted on robot end effector. Assuming that the force exerted on robot equals to the force exerted on human arm, namely \( \mathbf{f}_H = \mathbf{f}. \) Besides, we can also assume that robot actual position equal to compliant position, namely \( \mathbf{p} = \mathbf{p}_c. \) Combining (11) and (12) we have the following equation:

\[ M_d \ddot{\mathbf{e}} + D_d \dot{\mathbf{e}} + K_H \mathbf{e} = M_d \ddot{\mathbf{p}}_c + (D_d - D_H) \dot{\mathbf{p}}_c, \]  

(13)

where \( \mathbf{e} = \mathbf{p}_d - \mathbf{p} \) represents the error between desired position and robot actual position. From (13), it can be inferred that the robot manipulator can track human desired position accurately if human desired position is a constant. While usually the human desired position is time varying, thus a MRAC based compensation is introduced in this paper to assist human operator interact with the robot, so that the position tracking error can be eliminated. For simplicity, here we only consider in single direction. The compensation is expressed as follows:

\[ \mathbf{u}(t) = s(t) + l_v(t) \mathbf{e}(t) + l_d(t) \mathbf{e}^\prime(t). \]  

(14)

Substituting (14) into the error dynamics of (13) yields:

\[
\ddot{\mathbf{e}} + \frac{(D_d + l_d)}{M_d} \dot{\mathbf{e}} + \frac{(K_H + l_v)}{M_d} \mathbf{e} = \frac{M_d \ddot{\mathbf{p}}_c + (D_d - D_H) \dot{\mathbf{p}}_c - s}{M_d}
\]  

(15)

(15) can be simplified as follows:

\[
\ddot{\mathbf{e}} + a(t) \dot{\mathbf{e}} + b(t) \mathbf{e} = j(t).
\]  

(16)

The above equation is an adjustable system in the MRAC framework. The parameters of (14) are modulated as follows [13]:

\[
\dot{s} = -\frac{1}{L} \frac{d}{dt} q - L^* \frac{d}{dt} [q^e], \quad \dot{v}_c = \frac{1}{M} \frac{d}{dt} [\mathbf{e}^T \mathbf{q} - M^* \frac{d}{dt} [\mathbf{e}^T \mathbf{q}^e]]
\]

(17)

\[
\dot{\mathbf{d}} = \frac{1}{N} \frac{d}{dt} q^e - N^* \frac{d}{dt} [q^e],
\]

where \( q = we + v^e, L, L^*, M, M^*, N, N^*, w, v \) are positive scalars and they are determined by user.

Supposing the reference model is expressed as

\[
\ddot{\mathbf{e}} + 2\xi \Omega \dot{\mathbf{e}}_m + \Omega^2 \mathbf{e}_m = 0.
\]  

(18)

It represents the desired behavior of \( \mathbf{e}(t). \) Subtracting (18) from (16) we have the following equation:

\[
\dot{\mathbf{E}} = \begin{bmatrix} 0 & 1 & -\Omega^2 \\ 0 & 2\xi \Omega & -2\xi \Omega \\ -\Omega^2 & -2\xi \Omega & -\Omega^2 \end{bmatrix} E + \begin{bmatrix} 0 & 0 \\ \Omega^2 - b & 2\xi \Omega - a \end{bmatrix} \begin{bmatrix} \dot{\mathbf{e}} \\ \dot{\mathbf{e}}^T \\ \mathbf{e} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix} J,
\]

(19)

where \( E = e - \mathbf{e}_m. \)

**Theorem 2**: There exists a choice of parameters \( a \) and \( b \) updated by (17) that makes the origin of the state space for the augmented system (19) stable. Moreover if \( e \) is bounded, then \( E \to 0 \) as \( t \to \infty. \)

**Proof**: Select a Lyapunov candidate function as follows:

\[ V = E^T P E + L(f + L^* q)^2 + M(\Omega^2 - b + M^* q e^2)^2 + N(2\xi \Omega - a + N^* q e)^2, \]  

(20)

where \( P \in \mathbb{R}^{2 \times 2} \) is a constant symmetric, positive definite matrix and it satisfies the Lyapunov function for the reference model. Thus it has the following property:

\[ PA + (A^*)^T P = -Q, \]  

(21)
where $Q \in R^{2 \times 2}$ is a symmetric positive definite matrix. By differentiating (20) and letting $s = f$, $lv = a$, $ld = b$:

$$
\dot{V} = -E^TQE + [2\dot{Q}f(\dot{f} - 2Q\dot{q}) + 2gf - 2Q\ddot{q}] + 2Qf(b - \omega)^2(b - Q\dot{q}^2 - Q\dot{q}\dot{v} - 2Q\ddot{q}\dot{e} - 2Q\dddot{q})e - 2Qf(a - 2\omega\dot{q} - 2\xi\dot{e} - 2Q\dddot{q}\dot{e} - 2Q\dddot{q})e. $$

(22)

Substituting (17) into (22) yields

$$
\dot{V} = -E^TQE - 2Q\dot{q}^2 - 2Q\ddot{q}^2 - 2Q\dddot{q}^2 \leq 0.
$$

(23)

Thus the stability of the proposed method for the design of assist force compensation has been proved. Moreover, it is easy to demonstrate that $e$ is also bounded if $l_v$ and $l_d$ are bounded, $l_v$ and $l_d \in \mathcal{L}_e$, as described in (17). As a result, it follows that $e$ is uniformly continuous which leads to $E \to 0$ as $t \to \infty$. ■

3.2. SBL-Based Human Intention Prediction

![Robot manipulator and Human partner interacting](image)

Fig. 3 Human-robot interaction system

According to the previous section, it is obvious that it is necessary to know the human desired position before the design of force assist compensation. Human robot interaction is shown in Fig. 3. According to (10), the human desired position can be expressed in the form of a nonlinear time-varying function. For simplicity, we only consider the situation along single direction, namely x-axis:

$$
x_d = G(f_{H,x}, \dot{x}, x),
$$

(24)

where $x, \dot{x}, x_d, f_{H,x}$ represent the robot actual position, robot manipulator velocity, human desired position along x-axis and contact force along x-axis respectively.

Function $G(\cdot)$ can be transformed into a nonlinear autoregressive exogenous (NARX) model, thus the human desired position can be expressed in time series:

$$
A(z^{-1})x_d(k) = B^T(z^{-1})F^T(u(k)) + \zeta(k)
$$

(25)

with $A(z^{-1}) = 1 + a_1 z^{-1} + \cdots + a_n z^{-n}$

$$
B(z^{-1}) = 
\begin{bmatrix}
 b_1^1 & b_1^2 & \cdots & b_1^n \\
b_2^1 & b_2^2 & \cdots & b_2^n \\
\vdots & \vdots & \ddots & \vdots \\
b_m^1 & b_m^2 & \cdots & b_m^n
\end{bmatrix}
\begin{bmatrix}
 z^{-1} \\
 z^{-2} \\
 \vdots \\
 z^{-q}
\end{bmatrix},
$$

where $u(k) = [f_{H,x}(k), \dot{x}(k), x(k)]^T$ is input vector, which includes the force, velocity and position. $F(u(k)) = [f_1(u(k)), f_2(u(k)), \cdots, f_m(u(k))$ is a vector of dictionary functions. These dictionary functions are determined by user. $\zeta(k)$ is additive noise. (25) can be rewritten into the form:

$$
x_d(k) = w \Phi(k) + \zeta(k)
$$

$$
\Phi(k) = [\phi(k), \phi(k-1), \cdots, \phi(k-N-1)]
$$

(26)

$$
| \zeta(k) - 1| = [\zeta(k-1), \zeta(k-2), \cdots, \zeta(k-N)]^T
$$

where $\phi(k) = [y(k-1), y(k-2), \cdots, y(k-n), F_T(u(k-1)), F_T(u(k-2)), \cdots, F_T(u(k-q))]$ is a dictionary function vector with $q \leq n$. $w = [a_1, a_2, \cdots, a_n, b_1^1, b_1^2, \cdots, b_1^n, b_2^1, b_2^2, \cdots, b_2^n, \cdots, b_m^1, b_m^2, \cdots, b_m^n]$ is the weights vector of $\phi(k)$. $\zeta(k)$ is the noise vector and it is subjected to Gaussian distribution, namely $\zeta(k) \sim N(0, \Lambda)$. However, the weights to be identified are so many that it may leads to severe over-fitting. In order to avoid this situation, hyper parameters are introduced [16]. Thus the means and variance of the identified parameters can be expressed as follows (for details, see [16]):

$$
w^* = \beta \Sigma \Phi^T x_1,
$$

(27)

$$
\Sigma = (\beta \Phi^T \Phi + A)^{-1},
$$

where $A = diag(\alpha_1, \alpha_2, \cdots, \alpha_N)$. $\beta, \alpha_i$, $i = 1, 2, \cdots, N$ are hyper parameters and they are subjected to Gamma distribution. With the estimated weights according to (20), it is easy to make prediction of human desired position and the generalized predictive equation is shown as follows

$$
\dot{X}_d(k+1) = S_d \ddot{x}(k) + S_d U(k)
$$

(28)

where $\dot{X}_d(k+1) = \ddot{x}_d(k+1), \dot{x}_d(k+2), \cdots, \dot{x}_d(k+(H_p+1))$ is a vector consists the predicted outputs of next $H_p$ steps. $U(k) = [F_T(u(k)), F_T(u(k+1)), \cdots, F_T(u(k+H_u-1))]$ is an input vector of next $H_u$ steps with $H_u \leq H_p$. More details about matrices $A, B, C$ and $S_d \in R^{d \times N}, S_e \in R^{d \times N}$ can be found in our previous work [7]. Thus the SBL based human intention predictor has been developed in this section.

With the measurable contact force, robot Cartesian position and velocity in time series, the future human desired position can be predicted accurately. Then the predicted desired position is used for the
design of MRAC based assist force compensation. The effectiveness of this method will be illustrate in the simulation part.

4. SIMULATION STUDY

Fig. 4 Simulated 2-DOF robot manipulator

In this section, the proposed method is tested on a simulated 2-DOF robot manipulator. As shown in Fig.4, the robot end effector can move in x-y plane. The dynamic and kinetic models are described mathematically in Simulink. The parameters of the links are presented as follows: \( m_1 = m_2 = 1 \text{ kg} \), which stand for the mass of the two links. \( l_1 = l_2 = 1 \text{ m} \) are the length of link one and link two respectively. Here we ignore the inertia of the robot, namely \( I_1 = I_2 = 0 \). The proposed method is adopted to realize compliant behaviour between robot and human operator. The parameters are selected as follows: impedance parameters are selected as \( M_d = \text{diag}(0.005, 0.005) \) and \( D_d = \text{diag}(0.1, 0.1) \), and these parameters are kept as constants during interaction. Inner position loop parameters are selected as \( K_p = \text{diag}(1, 1) \) and \( K_d = \text{diag}(1, 1) \).

Outer force loop parameters are selected as follows: the parameters for MRAC based force compensation are: \( L = 0.2, L^* = 0, M = 0.1, M^* = 0, N = 0.1, N^* = 0, w = 2, v = 1 \). The parameters for SBL based human intention predictor are: \( n = N = H_p = H_u = 30, q = 1 \). Vector \( F(u(k)) \) is defined as \( f(k), f^2(k), p(k), p(k), p(k), p^2(k) \) and other nonlinear combinations of these terms. Human desired position \( x_d \) is predefined as a sine trajectory. Simulation time is 20 s and time step is chosen as 0.008s. The predictor does not work in the first 1s because it needs time to accumulate enough data in time series. All of the results are shown in the figures below by comparing operating force and tracking performance between the compensated method and without compensation.

In the simulation study, the motion of the robot is considered along single direction, namely x-axis. The simulation results of human intention prediction using the proposed method is shown in Fig.5. It can be inferred that with the necessary information in time series, the SBL based human intention predictor can predict the future desired position accurately. The prediction error is shown in Fig.6. Trajectory tracking results are shown in Fig.7. There is an obvious time delay in the tracking result without force compensation, while the delay can be mitigated using the proposed method. The comparison between operating force of proposed method and that of no compensation is shown in Fig.8. According to these results, we shall conclude that the proposed method is effective for HRI tasks. Compared with the sit-
vation without compensation, the proposed method can achieve trajectory tracking better with smaller operating force.

5. CONCLUSION

The contributions of this paper are presented as follows: (I) A novel HRI framework is proposed, which includes an inner position loop and an outer force loop. (II) For inner loop, the Cartesian drive torque for an n-DOF robot manipulator has been analyzed and a PD based controller with gravity compensation is adopted to generate the drive torque. (III) For outer loop, a MRAC based force compensation method is proposed to eliminate time-delay during HRI, for the sake of acquiring future human desired position, a SBL based human intention predictor is also adopted in outer loop. The results indicate that our method has good performance in physical human-robot interaction process. Operating force and trajectory tracking error are reduced significantly compared with the situation without our method. Besides, the SBL based human intention predictor is effective and it can predict human desired position with high accuracy.

For the future work, the inner position loop will be developed to meet the existence of unknown disturbance. So the HRI will be more stable and safer.

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