Dual-Loop Iterative Learning Control of Robot Manipulator for Human-Robot cooperation

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Abstract. This paper proposed a dual-loop iterative learning control strategy for robot manipulator in the situation of repetitive human-robot interaction. By utilizing the contact force between the human and the manipulator, a force-based loop is first conducted to produce the unknown desired trajectory of the manipulator. According to Lyapunov’s method and using the back-stepping technique, an adaptive iterative learning controller is presented to fulfill the trajectory tracking task of the robot manipulator, in spite of the model uncertainties and the unknown disturbances. The proposed control scheme is verified by numerical simulation on a robot manipulator with two degrees-of-freedom.

1. INTRODUCTION
AS a labour-replacing machinery, robots in traditional structured environment fully meet the production requirements of signal mode. It has played a critical role in social progress and economic development. However, with the innovation of manufacturing mode and the expansion of product application field, the market demand is changed from large batch and single mode to small batch and diversified direction. Many manufacturing tasks are too complex to be automatically completed by robots. An increasing number of production processes require the robots and humans to cooperate to complete tasks. In this context, human-robot cooperation is becoming more and more important and has acquired wide-ranging attentions. Human-robot cooperation has the complementary advantages of both mechanical endurance and human intelligence[1]. The robot is good at performing predefined tasks with stable performance, while the human being with their natural intelligence is skilled in handling unstructured environments.

From the perspective of control process, the robot is driven by its actuator system with certain control algorithm. One of the most vital technologies on the control of human-robot cooperation is to obtain the human partner’s motion trajectory, so that the robot manipulator can follow the human’s movement smoothly and finish the task with the partner collectively. It should be noted that, the partner’s movement is not invariant and unknown to the robot control system in every working cycle due to the subjective consciousness of human. It is not realizable for the robot manipulator to track a predefined trajectory. Impedance control [2] is one of the solutions to this problem. In [3], the force tracking control of a robot manipulator is addressed. Both torque-based and position-based impedance control are implemented for the robot, and the uncertainties in the robot model is compensated by...
applying neural network technique. In [4], a simple impedance control scheme is proposed to track a specified force and compensate for uncertainties in environment location and stiffness. By using an adaptive technique, the force error is minimized. The effectiveness of the proposed method is verified by simulation on a three-link rotary robot manipulator. In [5], coordination control of a dual-arm robot is investigated impedance transference. An adaptive impedance controller is proposed in the task space to drive the slave arm tracking the desired trajectory. In [6], an experimental study on human-robot comanipulation with kinematic redundancy is presented. Cartesian impedance control is used to promote the performance during human-robot cooperation by combining the impedance modulation and redundancy resolution. However, the above researches reveal the disadvantage of impedance on maintaining the robustness of a control system[7]. To solve this problem, the human partner’s motion trajectory is expected to be gauged and incorporated into the control system.

Numerous manufacturing processes exhibit repeatability in both the time and space domain. For instance, the same batch of products always spend the same and share the same space in manufacturing. Inspired by this, the usage of repetitive characteristics of the robot manipulator is expected to improve the performance of the control system with human-robot cooperation. Iterative learning control is one of the noted methods to deal with periodic tracking problems and learn the repetitive uncertainties and unknown disturbances[9]-[11]. In [12], a comprehensive iterative learning framework is formulated for a gantry robot with mixed system constraints. The iterative learning algorithm is obtained by applying the successive projection method. In [13], three iterative learning control schemes are presented for trajectory tracking of rigid robot manipulators with unknown parameters. These controllers are conducted and well arranged with different prior information. In [14], a combination of iterative learning and model-based control is presented for direct-drive robots to achieve high quality motion control. The unknown model parameters are estimated on line by a batch-adaptive algorithm. In [14], the tracking control problem of a class of multi–input–multi–output mismatched systems is discussed. Reference and torque iterative learning controllers are designed for different injection locations in the closed-system to achieve high tracking performance for the out of interest.

In this paper, the trajectory tracking problem for a robot manipulator performing repetitive tasks with human partner is studied through a dual-loop iterative learning control scheme. The inconsistent desired trajectory caused by the human is estimated in the first loop via applying the contact force between the robot and the partner. Then, by introducing an adaptive iterative algorithm in the second loop, the robot is driven to track the desired trajectory in spite of model uncertainties and unknown disturbances. The remaining sections of this paper are organized as follows. The system description and problem formulation are addressed in Section II. Then, the dual-loop iterative learning controller is presented in Section III. In Section IV, numerical simulations are carried out to verified the effectiveness of the control scheme. Section V concludes the work.

### 2. SYSTEM DESCRIPTION AND PROBLEM FORMULATION

#### 2.1. System Description

The model of a n-link robot manipulator cooperates with a human partner can be expressed as [16]

\[
D(\theta_1)\ddot{\theta}_1 + C(\theta_1, \dot{\theta}_1)\dot{\theta}_1 + G(\theta_1) = \tau_i + f_i(t) + \eta_i(t)
\]

(1)

where \( k \geq 0 \) is the iteration number, \( \theta_1, \dot{\theta}_1, \) and \( \ddot{\theta}_1 \), are the angle vector, the velocity vector, and the acceleration vector of the joints, respectively. \( D(\theta_1), C(\theta_1, \dot{\theta}_1), G(\theta_1) \), are the inertia matrix, the centrifugal-Coriolis matrix, and the gravity vector, respectively. \( \tau_i \) is the torque of the robot manipulator, \( f_i(t) \) is the interaction force between the robot and its partner, and \( \eta_i(t) \) is the model uncertainties and disturbances. \( t \in [0, T] \) is the finite operation time in every process.

For the above robot system, the following properties and assumption are considered [17].
Property 1. The matrix $D(\theta) - 2C(\theta, \dot{\theta})$ is a skew symmetric matrix which satisfies for any $x$ and $\theta$.

$$x^T \begin{bmatrix} D(\theta) - 2C(\theta, \dot{\theta}) \end{bmatrix} x = 0 \quad (2)$$

Property 2. For known functions $\varepsilon$ and its derivative $\dot{\varepsilon}$, there has a unknown vector $\xi(t)$, such that where $\Psi(\theta, \dot{\theta}, \varepsilon, \dot{\varepsilon})$ is a known regression matrix.

$$D(\theta) \dot{\varepsilon} + C(\theta, \dot{\theta}) \varepsilon + G(\theta) = \Psi(\theta, \dot{\theta}, \varepsilon, \dot{\varepsilon}) \xi(t) \quad (3)$$

Assumption 1. The model uncertainties and disturbances, $\eta(t)$, is bounded in the following sense where $\bar{\eta}(t)$ is a known upper bound.

$$\|\eta(t)\| < \bar{\eta}(t) \quad (4)$$

2.2. Problem Formulation

For a robot manipulator in traditional structured environment, the desired trajectory is predefined and available for the control development. However, in the human-robot cooperation situation considered in this paper, the desired trajectory of the robot manipulator is generated by its human partner, and is unavailable for the control system. Actually, when a robot manipulator cooperating with human, the robot arm is piloted by the interaction force between the robot and the human’s limb. The interaction force of a human limb can be expressed as the following model [16] where $C_H$, $G_H$ are the damper

$$-C_H \dot{\theta} + G_H (\theta - \theta_h) = f(t) \quad (5)$$

and spring matrices of the human limb. $\theta_h$ is the motion intention planed by the human partner.

According to the interaction force of human limb in (5), a target training force $f_d(t)$ will involve in a desired trajectory $\theta_d$, which can be demonstrated as the desired trajectory $\theta_d$ can be obtained according to the human intention $\theta_h$ by using equation (6).

$$-C_H \theta + G_H (\theta - \theta_h) = f_d(t) \quad (6)$$

However, $\theta_h$ is generated by the human’s nervous system and is unknown for the robot control system. The primary work of the control design we need to do in this paper is to estimated the desired trajectory $\theta_d$.

Considering the repetitive situation of the manufacturing process, the following reasonable assumption is given to facilitate the control design.

Assumption 2. The pilot’s intention $\theta_h$ is bounded by $\| \theta_d \| < c_{max}$ where $c_{max}$ is the boundary, and is repeatable over $[0, T]$ where $k$ is the iteration index.

$$\theta_{hk}(t) = \theta_{hk,i}(t), \quad t \in [0, T] \quad (7)$$

Equation (7) shows the repetitive characteristic of the human intention, this is acceptable because the pilot is required to achieve an efficient production process.

3. CONTROL DESIGN

This section will give the development of the dual-loop iterative leaning control scheme. First, the robot’s desired trajectory will be estimated by applying the contact force between the robot and the human partner in a learning way. Then, based on the estimated desired trajectory and using the back-stepping technology under the framework of Lyapunov method, the adaptive iterative learning
controller will be designed to perform the human-robot cooperation and deal with the system uncertainties and disturbances.

3.1. Desired Trajectory Estimation

According to equation (5) and (6), if we subtract \( f(t) \) in (5) by \( f_d(t) \) in (6), we obtain from (8),

\[
-C_H (\dot{\theta} - \dot{\theta}_d) + G_H (\theta - \theta_d) = f(t) - f_d(t)
\]

we can observe that the sum of \( \theta - \theta_d \) and its first-order derivative are proportional to \( f(t) - f_d(t) \).

Thus, it is trustworthy for us to estimated the robot’s desired trajectory \( \theta_d \) in the following manner

\[
\theta_{r,i} = \theta_{r,i-1} + \lambda (f_d(t) - f(t))
\]

where \( i \) is the iterative number, and \( \lambda \) is a learning gain matrix.

3.2. Adaptive Iterative Learning Control Design

Define the state variables \( x_{1,i} = \dot{x} \) and \( x_{2,i} = \ddot{x} \), we can rewrite the dynamics of the robot manipulator cooperates with a human partner (1) in the state space as

\[
\begin{bmatrix}
\dot{x}_{1,i} = x_{2,i} \\
\dot{x}_{2,i} = D(x_{1,i})^{-1} \left[ \tau_i + f_i(t) + \eta_i(t) - C(x_{1,i}, x_{2,i}) x_{2,i} - G(x_{1,i}) \right]
\end{bmatrix}
\]

According to the Lyapunov method and using the backstepping technology, an adaptive iterative controller is proposed along the following steps.

**Step 1:** Introducing the following errors

\[
\begin{cases}
\epsilon_{1,i} = x_{1,i} - x_{1r,i} \\
\epsilon_{2,i} = x_{2,i} - \alpha_i
\end{cases}
\]

Where \( x_{1r,i} = \theta_{r,i} \), \( \theta_r \) is the estimation of \( \theta_d \), and \( \alpha_i \) is a virtual controller which will be designed.

Taking the derivative of \( \epsilon_{1,i} \), we have

\[
\dot{\epsilon}_{1,i} = \dot{x}_{1,i} - \dot{x}_{1r,i} = x_{2,i} - \dot{x}_{1r,i} = \epsilon_{2,i} + \alpha_i - \dot{x}_{1r,i}
\]

The virtual controller \( \alpha_i \) is designed as

\[
\alpha_i = -k_i \epsilon_{1,i} - \dot{x}_{1r,i}
\]

Substituting (13) into (12), \( \dot{\epsilon}_{1,i} \) can be rewritten as

\[
\dot{\epsilon}_{1,i} = \epsilon_{2,i} + (-k_i \epsilon_{1,i} - \dot{x}_{1r,i}) - \dot{x}_{1r,i} = -k_i \epsilon_{1,i} + \epsilon_{2,i}
\]

Choose a Lyapunov function candidate as

\[
V_{1,i} = \frac{1}{2} \epsilon_{1,i}^T \epsilon_{1,i}
\]

Considering the derivative of (15) and combining (14), we obtain

\[
\dot{V}_{1,i} = \epsilon_{1,i}^T \dot{\epsilon}_{1,i} = \epsilon_{1,i}^T (-k_i \epsilon_{1,i} + \epsilon_{2,i})
\]

\[
= -k_i \epsilon_{1,i}^T \epsilon_{1,i} + \epsilon_{1,i}^T \epsilon_{2,i}
\]

**Step 2:** According to (10) and (11), the time derivative of \( \epsilon_{2,i} \) is

\[
\dot{\epsilon}_{2,i} = \ddot{x}_{2,i} - \dot{\alpha}_i
\]

\[
= D(x_{1,i})^{-1} \left[ \tau_i + f_i(t) + \eta_i(t) - C(x_{1,i}, x_{2,i}) x_{2,i} - G(x_{1,i}) \right] - k_i \epsilon_{1,i} + \ddot{x}_{1r,i}
\]

Choose another Lyapunov function candidate as
Calculating the derivative of (18), one can get

\[ \dot{V}_{2,j} = \frac{1}{2} \epsilon_{2,j}^T D(x_{1,j}) e_{2,j} \]  

(18)

Now, the adaptive iterative learning controller is designed as

\[ \dot{\tau}_i = -\epsilon_{i,j} - k_2 e_{2,j} - f_i(t) - \text{sgn}(e_{2,j}) m(t) + \Psi_i(t) \]  

(22)

The updating law of \( \xi_i(t) \) is given as

\[ \dot{\xi}_i = \dot{\xi}_{k-1} + k_3 \Psi_i(t)^T e_{2,i} \]  

(23)

where k3 is the learning gain. Substituting (22) into (21) yields
\begin{equation}
\dot{V}_{2j} = e_{2j}^T \left(-e_{ij} - k_2 e_{2j} - f_i(t) - \text{sgn}(e_{2j}) \bar{\eta}_i(t)\right)
+ \Psi_i(t) \dot{\xi}_i(t) + f_i(t) + \eta_i(t) + \Psi(t) \dot{\xi}(t)
= e_{2j}^T \left(-e_{ij} - k_2 e_{2j} - \text{sgn}(e_{2j}) \bar{\eta}_i(t) + \eta_i(t) + \Psi(t) \dot{\xi}(t)\right)
\end{equation}

where \(\ddot{\xi}_i(t) = \dot{\xi}_i + \ddot{\xi}(t)\) is the estimation error. Let
\begin{equation}
V_i = V_{1j} + V_{2j}
\end{equation}

According to (16) and (24), we have
\begin{align}
\dot{V}_i &= \dot{V}_{1j} + \dot{V}_{2j} \\
&= -k_1 e_{1j}^T e_{1j} + e_{1j}^T e_{2j} + e_{2j}^T \left(-e_{ij} - k_2 e_{2j} - \text{sgn}(e_{2j}) \bar{\eta}_i(t) + \eta_i(t) + \Psi(t) \dot{\xi}(t)\right)
\leq -k_1 e_{1j}^T e_{1j} - k_2 e_{2j}^T e_{2j} + e_{2j}^T \Psi(t) \dot{\xi}(t) + ||e_{2j}|| \eta_i(t) + \text{sgn}(e_{2j}) \bar{\eta}_i(t)
\leq -k_1 e_{1j}^T e_{1j} - k_2 e_{2j}^T e_{2j} + e_{2j}^T \Psi(t) \dot{\xi}(t)
\end{align}

### 3.3. Main Results

**Theorem 1**: Considering the robot manipulator (1) in the situation of repetitive human-robot interaction under Property 1-2 and 1-2, when the dual-loop controller (22) and (9) are applied, 1) the tracking error \(e_{1j}\) and \(e_{2j}\) converges to zero asymptotically along the iteration axis, i.e. \(\lim_{k \to \infty} e_{1j} = 0; \lim_{k \to \infty} e_{2j} = 0\); 2) the interaction force \(f_i(t)\) converges to \(f_d(t)\) asymptotically, i.e., \(\lim_{k \to \infty} [f_i(t) - f_d(t)] = 0\).

Proof: We only address the proof of the interaction force here due to the page limitation. The convergence of the tracking error can be concluded by using the similarly way in the literatures, like [19] and [13].

Define the Lyapunov function as
\begin{equation}
V_{fj}(t) = \frac{1}{2\lambda_{\max}} \int_0^r (\theta_{ij} - \theta_{di})^T (\theta_{ij} - \theta_{di}) dt
\end{equation}

where \(\gamma_{\max}\) is the maximum value of \(\gamma_i, i = 1, \ldots, n\). The difference of \(V_{fj}\) is
\begin{align}
\Delta V_{fj}(t) &= V_{fj}(t) - V_{fj-1}(t) \\
&= -\frac{1}{2\gamma_{\max}} \int_0^r (\theta_{ij} - \theta_{di})^T (\theta_{ij} - \theta_{di}) dt - \frac{1}{2\lambda_{\max}} \int_0^r (\theta_{ij} - \theta_{di})^T (\theta_{ij} - \theta_{di}) dt + \frac{1}{2\lambda_{\max}} \int_0^r (\theta_{ij} - \theta_{di})^T (\theta_{ij} - \theta_{di}) dt
\end{align}

Looking back on Assumption 1 and (6), we get \(\theta_{di} = \theta_{dk-1}\). Then, (28) can be rewritten as
\begin{align}
\Delta V_{fj}(t) &= -\frac{1}{2\lambda_{\max}} \int_0^r (\theta_{ij} - \theta_{di})^T \bar{\theta}_j dt + \frac{1}{2\lambda_{\max}} \int_0^r (\theta_{ij} - \theta_{di})^T \bar{\theta}_j dt + \frac{1}{2\lambda_{\max}} \int_0^r (\theta_{ij} - \theta_{di})^T \bar{\theta}_j dt
\end{align}
\[
\begin{align*}
\Delta V_{f_d}(t) & \leq \int_0^T \left( K(f_i(t) - f_d(t)) - e_i^T \left[ f_d(t) - f_i(t) \right] \right) dt \\
& \leq \int_0^T \left( f_i(t) - f_d(t) \right)^T \left( f_i(t) - f_d(t) \right) dt - \int_0^T e_i^T \left( f_i(t) - f_d(t) \right) dt 
\end{align*}
\]

Since \( e_i \) converges to zero, thus we have

\[
\Delta V_{f_d}(t) \leq -K \int_0^T \left( f_i(t) - f_d(t) \right)^T \left( f_i(t) - f_d(t) \right) dt
\]

Considering the definition of \( V_{f_d}(t) \) in (27), we can conclude that \( \theta_{r,i} \rightarrow \theta_{d,i} \) and thus \( f_i(t) \rightarrow f_d(t) \) when \( k \rightarrow \infty \).

4. SIMULATION STUDY

The proposed dual-loop iterative learning controller is tested by numerical simulation on a robot link with two degrees-of-freedom in this section. The matrix \( D(\theta) = \begin{bmatrix} D_{ij} \end{bmatrix}_{2 \times 2} \) is given by

\[
D_{11} = m_1 l_1^2 + m_2 \left( l_1^2 + l_2^2 + 2l_1l_2 \cos(x_{12,i}) \right), \quad D_{12} = D_{21} = m_2 \left( l_2^2 + l_1l_2 \cos(x_{12,i}) \right), \quad D_{22} = m_2 d_2^2.
\]

The Coriolis matrix \( C(\theta, \dot{\theta}) = \begin{bmatrix} C_{ij} \end{bmatrix}_{2 \times 2} \) is given as

\[
C_{11} = -m_2 l_2 \sin(x_{12,i}), \quad C_{12} = -m_2 l_2 \left( x_{21,i} + x_{22,i} \right) \sin(x_{12,i}), \quad C_{21} = m_2 l_1 \sin(x_{12,i}), \quad C_{22} = 0.
\]

The parameter values are chosen as \( m_1 = 2.2 \text{ kg} \), \( m_2 = 1.8 \text{ kg} \), \( l_1 = 45 \text{ cm} \), \( l_2 = 38 \text{ cm} \), \( g = 9.8 \text{ N/kg} \). The exoskeleton’s initial reference trajectories for rehabilitation are given as \( \theta_{r,0} = \sin(2\pi t) \) and \( \theta_{r,0} = \cos(2\pi t) \), respectively.

The control parameters are set to \( k_1 = 12 \), \( k_2 = 20 \), \( k_3 = 50 \), and \( \lambda = 25 \). Simulation results with ten iterations are presented in Fig. 1 and Fig. 2. In Figure 1, the tracking error converges to error with the increasing of the iterative number. In Figure 2, despite the tracking error of the interaction force have not reached zero in finite interactive number, it is remarkably decreased along the iteration axis.

5. CONCLUSION

The trajectory control of robot manipulator with repetitive human-robot interaction is investigated in this paper. A dual-loop controller is proposed to perform the trajectory tracking task. The first loop is constructed by the contact force between the human and the manipulator to produce the unknown desired trajectory of the manipulator. The second loop is designed by using an adaptive iterative learning algorithm. With the adaptive updating law, the controller can also deal with the system uncertainties and external disturbances. The convergence of the error of the interaction force is proved by a Lyapunov way. Numerical simulation results reveal the efficiency of the proposed controller.
Figure 1. The trajectory tracking errors with 10 iterations.

Figure 2. The force tracking errors with 10 iterations.

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