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Neural impedance adaption for assistive human–robot interaction

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ABSTRACT

The problem of assistive human–robot interaction (HRI) with unknown impedance parameters is non-trivial and interesting. This problem becomes even more challenging if unknown reference trajectory and uncertain robot dynamics are involved. This study investigates an intelligence impedance adaption control scheme to assist human interaction with an unknown robot system. An algorithm is proposed to facilitate assistive HRI by optimizing the overall human–robot interaction performance. Neural networks (NN) and backpropagation are employed to tackle the optimization problem, based on an online adaption of impedance parameters. The tuned impedance model is integrated into the design of the neuroadaptive controller. The controller is modified by utilizing the barrier Lyapunov function technique to increase the safety, and to improve functionality of the NN during the system operation. The obtained controller can learn the robot dynamics online while coping with both the problems of trajectory-following and impedance model-following. Stability and uniform boundedness of the closed-loop system are verified through Lyapunov direct analysis. The effectiveness of the proposed control design is validated by theoretical analysis and numerical simulation.

1. Introduction

Impedance control that aims to control the dynamic behavior has recently gained increasing importance as the focus of robotic applications shifts from industrial robots to social ones. In fact, as daily applications such as elderly care, health care, and education make their way into the robotic research, the control of motion/force became inadequate to handle the interaction task. Instead, impedance control and specifically adaptive impedance control that aims to provide safety and to reduce dependency on precise knowledge of the robot dynamics has undergone rapid progress over the past decade.

1.1. Related works and motivation

In several studies on impedance control, a desired fixed passive impedance model was prescribed, and then efforts were focused on some challenges like handling the uncertainties. Works which fall under this framework typically have employed learning impedance control [1], or adaptive impedance control [2]. However, assuming fixed impedance models is no longer sufficient to describe some applications like explosive movement [3], or HRI [4]. Accordingly, employing variable impedance control must be considered [3,4]. Nevertheless, to achieve improved interaction performance, it appears more effective to tune impedance parameters to provide optimal impedance characteristics, which are required for such important applications like HRI. In [5] adaptive impedance motion learning for physical HRI was presented. In this study, robot anticipated the partner’s intentions to adapt the motion by task learning. Optimal impedance adaptation was studied for constrained motion HRI in [6]. Continuous critic learning was utilized for interaction control then, the desired impedance was obtained to be used as an optimal realization for satisfying control objective.

In the development of HRI with unknown impedance models, methods like impedance learning or impedance adaption have been investigated. Starting from the 1984 seminal works by Arimoto et al. [7,8] several researchers employed iterative learning control to obtain impedance parameters in designing robot controls. This method was based on the notion that improvement of performance can be achieved by repeating a task and learning from previous executions. In [9] a two-loop impedance learning control framework was studied to solve the robot-environment interaction problem. An adaptive control was utilized for the inner-loop position control. Desired impedance model were obtained using the gradient-following and betterment schemes via minimizing a cost function is minimized. Surveys on iterative learning control with the brief categorization of the method can be found in

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[10–12]. However, as this method makes the robot repeat operations to learn the desired impedance parameters, it may cause inconvenience in several situations, specifically when online or complex tasks are required.

Compared to iterative impedance learning methods, in the impedance adaptation method, impedance parameters can be tuned without requiring the operation to be repeated [13]. However, developing an adaptive scheme is a challenging issue. In this method, to adjust the impedance parameters, several concerns can be raised regarding the improvement of system performance e.g. the input torque [14], the stability [15], minimizing a cost function [16], and developing assistive HRI [17,18]. Moreover, many techniques have been employed to solve the problem of finding impedance parameters. Moreover, many techniques have been employed to solve the problem of finding impedance parameters. Ge et al. used adaptive dynamic programming for impedance adaptation in an optimal robot–environment interaction [13]. Li et al. employed approximate dynamic programming to find impedance parameters in the shared control of human and robot [19]. Modares et al. employed reinforcement learning to obtain optimized assistive HRI in [18]. Game theory was utilized to solve the problem of impedance parameters finding in continuous role adaptation for human–robot shared control [20], and adaptive optimal control for coordination in physical HRI [21]. This method was also combined with policy iteration to obtain impedance parameters for human–robot coordination in [22].

The aim of control design in this paper is to propose a stable, intelligent assistive HRI scheme with unknown robot dynamics and impedance behavior. The method is based on neural adaptive impedance control, and future backpropagation methods to find impedance parameters. The control structure consists of two control loops, namely an inner-loop and an outer-loop. The former is designed to provide a constrained torque controller to make unknown robot dynamics respond like a prescribed robot impedance model without knowing the reference trajectory. The latter is exploited to afford assistive HRI by adjustment of impedance parameters.

1.2. Contributions and structure of the paper

The contributions of this paper can be highlighted as follows:

1. A neural adaptive impedance control is developed for an uncertain robotic system with unknown impedance model, by introducing a new inner-loop, outer-loop control structure.
2. An Inner-loop controller is designed to make an unknown robot behave like an impedance model with unknown reference trajectory. The presented controller does not require adapting robot impedance model parameters in this control loop. In addition, safe and constrained control is designed by utilizing the advantages of the barrier Lyapunov functions.
3. An outer-loop controller is designed to tune unknown impedance parameters such that assistive HRI is directed. To do this, NN and the backpropagation method are utilized to minimize the cost function in terms of the trajectory-following error and the interaction force.

The rest of the paper is organized as follows. In the next section, the dynamics of the robot and human limb model are described, and control objective of the paper is discussed. Section 3 presents the HRI control structure; first, the overall structure of the developed approach is briefly discussed then, the inner-loop and outer-loop control designs are detailed. Simulation results are presented in Section 4, and finally Section 5 concludes this paper.

Notations:

Throughout this paper, $\mathbb{R}$ and $\mathbb{R}^+$ are used to denote the sets of real numbers and non-negative real numbers, respectively. $(\tilde{\bullet}) = (\bullet^*) - (\hat{\bullet})$, with $(\hat{\bullet})$, and $(\bullet^*)$ represent estimated, and optimal values of $(\bullet)$, respectively. Vertical bars $\|\bullet\|$ denote the Euclidean norm for vectors or the Frobenius norm for matrices, $\lambda_{\min}(\bullet)$ and $\lambda_{\max}(\bullet)$ represent the smallest and largest eigenvalues of a square matrix $(\bullet)$, respectively.

2. System overview and preliminaries

2.1. System description

A system where a robotic arm physically interacts with a human is studied in this paper. Consider the dynamic model of robot manipulator in the Cartesian space as [23]:

$$\boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{x}} + \boldsymbol{C}\big(\boldsymbol{q},\dot{\boldsymbol{q}}\big)\dot{\boldsymbol{x}} + \boldsymbol{G}(\boldsymbol{q}) = \boldsymbol{\tau} + \boldsymbol{f_H}, \tag{1}$$

where $\boldsymbol{M} = \boldsymbol{J}^{-\boldsymbol{T}}\bar{\boldsymbol{M}}\boldsymbol{J}^{-1}$, $\boldsymbol{C} = \boldsymbol{J}^{-T}(\bar{C} - \bar{M}J^{-1}\dot{J})J^{-1}$, $\boldsymbol{G} = \boldsymbol{J}^{-\boldsymbol{T}}\bar{\boldsymbol{G}}$, $\boldsymbol{\tau} = \boldsymbol{J}^{-\boldsymbol{T}}\bar{\boldsymbol{\tau}}$, $\boldsymbol{q} \in \mathbb{R}^n$ is the generalized joint coordinate vector with $\boldsymbol{n}$ number of joints, $\boldsymbol{x} \in \mathbb{R}^n$ is the end-effector Cartesian position, $\boldsymbol{J} \in \mathbb{R}^{n\times n}$ is the Jacobian matrix, $\bar{\boldsymbol{M}} \in \mathbb{R}^{n\times n}$ denotes the mass (inertia) matrix, $\bar{\boldsymbol{C}} \in \mathbb{R}^{n\times n}$ represents the centrifugal and Coriolis forces matrix, $\bar{\boldsymbol{G}}(\boldsymbol{q}) \in \mathbb{R}^n$ is the vector of gravitational forces/torques; $\bar{\boldsymbol{\tau}} \in \mathbb{R}^n$ is the vector of generalized continuous torques acting at the joints, and $\boldsymbol{f_H}$ is the interaction force between the human and robot. Note that the robot manipulator dynamics in (1) are assumed to be unknown.

Property 1 [24]. The inertia matrix $\boldsymbol{M}$ is symmetric and positive definite. Also, the matrix $2\boldsymbol{C} - \dot{\boldsymbol{M}}$ is a skew symmetric matrix if $\bar{\boldsymbol{C}}$ is in the Christoffel form, i.e. $\Theta^T(2\boldsymbol{C} - \dot{\boldsymbol{M}})\Theta = 0$, $\forall \Theta \in \mathbb{R}^n$.

2.2. Problem statement

The main objective of control architecture in this paper is to design the force $\boldsymbol{\tau}$ in (1) to let the robot move along a desired trajectory $\boldsymbol{x_d}$ while the interaction force $\boldsymbol{f_H}$ is minimized, and the robot dynamics (1) respond like the following target impedance model:

$$\boldsymbol{M_r}\ddot{\boldsymbol{x}}_{\boldsymbol{b}} + \boldsymbol{B_r}\dot{\boldsymbol{x}}_{\boldsymbol{b}} + \boldsymbol{K_r}\boldsymbol{x_b} = \boldsymbol{f_H}, \tag{2}$$

where $\boldsymbol{x_b} = \boldsymbol{x_m} - \boldsymbol{x_d}$ with $\boldsymbol{x_m}$ being the unknown reference trajectory; $\boldsymbol{M_r}$, $\boldsymbol{B_r}$, and $\boldsymbol{K_r}$ are unknown desired inertia, damping, and stiffness parameter matrices, respectively. To satisfy the control objective design, we define the model-following error variable to be $\boldsymbol{e}_1 = \boldsymbol{x_m} - \boldsymbol{x}$, and the trajectory-following error to be $\boldsymbol{e}_2 = \boldsymbol{x_m} - \boldsymbol{x_d} = \boldsymbol{x_b}$ which is to be minimized. Also, an algorithm is designed to minimize $\boldsymbol{f_H}$ by properly modifying the impedance model parameters.

Assumption 1. The desired trajectory $\boldsymbol{x_d}$, and the reference trajectory $\boldsymbol{x_m}$ are bounded.

Remark 1. The selection of impedance model parameters $\boldsymbol{M_r}$, $\boldsymbol{B_r}$, and $\boldsymbol{K_r}$ depends on different applications. In particular, as the reference model (2) defines a desired dynamic relationship between the model-following error and the interaction force, choosing a passive impedance model is too conservative [13]. This paper aims to find the critical impedance parameters by optimizing the overall HRI performance. Accordingly, the assistive human–robot interaction can be conducted by updating the impedance parameters.

Remark 2. The relation between $\boldsymbol{e}_1$ and $\boldsymbol{e}_2$ can be established as $\boldsymbol{e}_2 = \boldsymbol{e}_1 + \boldsymbol{x} - \boldsymbol{x_d}$. Accordingly, in view of Assumption 1, it holds that if $\boldsymbol{e}_1 \in \ell_\infty$, then $\boldsymbol{x}$ is bounded, and accordingly $\boldsymbol{e}_2 \in \ell_\infty$ can be concluded. Thus, the key in designing the tracking control scheme is to ensure the boundedness of $\boldsymbol{e}_1$ which is addressed in the inner loop control design.

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