# ROLE ADAPTIVE ADMITTANCE CONTROLLER FOR HUMAN-ROBOT CO-MANIPULATION

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**Abstract**— To both decrease the physical toll on a human worker, and increase a robot's environment perception, a human-robot dyad may be used to co-manipulate a shared object. Most of the control strategies assign to the robot the role of a follower to the human's actions even though there are situations in which the human may benefit from robot leadership.

In order to emulate the human behavior during a co-manipulation task, an admittance controller with varying stiffness is presented here. The stiffness is continuously varied based on a scalar and smooth function that assigns a degree of leadership to the robot. Furthermore, the controller is evaluated through robot simulation environments, and its stability is analyzed using Lyapunov.

Keywords— Physical human-robot interaction, Adaptive admittance control, Co-Manipulation, Human-Robot collaboration.

**Resumo**— Para tanto diminuir o esforço físico de um humano, quanto aumentar a percepção de um ambiente por um robô, um díade humano-robô pode ser usado para co-manipulação de um objeto compartilhado. A maioria das estratégias de controle existentes atribuem ao robô a tarefa de seguidor das ações do humano mesmo que existam situações em que o humano possa se beneficiar da liderança do robô.

Para emular o comportamento humano durante uma tarefa de co-manipulação, um controle por admitância com rigidez variável é apresentado neste trabalho. A rigidez é continuamente variada com base em uma função escalar suave que define o grau de liderança do robô. Além disso, o controlador é avaliado por meio de simulações e sua estabilidade é analizada por uma função de Lyapunov.

**Palavras-chave** Interação física humano-robô, Controle por admitância adaptativo, Co-Manipulação, Co-laboração humano-robô.

### 1 Introduction

Human-robot co-manipulation is the manipulation of an object which is shared between a human agent and a robot agent. In this sort of manipulation the robot has to take into account several issues beyond the task execution, which include: human comfort, intentions of movement communication; or human safety. Most of the research in dyadic human-robot co-manipulation has focused on asymmetric relationships in between humans and robots, prioritarily treating a robot as a slave/follower. Jarrasse et al. (2014) suggests that efficient collaboration can be achieved by switching roles (leader/follower) between the robot and its human partner at some points in time.

The work in Cherubini et al. (2016) swaps the usual roles, assigning the robot as leader, giving the robot its own trajectory to track, but it also enables the robot to deviate from its own trajectory based on visual and haptic cues communicated by the human partner. The robot calculates the deviation based on an admittance control that can be used by a regular robot with joints controlled by position and not torque.

In Navarro et al. (2016), the authors use an adaptive admittance control law, that as in Cherubini et al. (2016) also requires compliance to the standard ISO10218-1.

Other authors also approach the problem by using impedance/admittance control schemes.

Moertl et al. (2012) for instance, developed dynamic role allocation strategies that continuously share the required effort (force/torque) among the partners in a dyad that cooperatively manipulated a table. The role allocation, described the leadership as a matter of voluntary effort in a preset direction that is redundant for both partners, that is, each partner could act in the redundant direction independently. If one of the partners was to act solely as a leader of the task, the entire required effort would be expected of it.

The idea that both partners in the dyad behave in between the extremes of pure leader or pure follower is also explored in Evrard and Kheddar (2009a), Evrard and Kheddar (2009b), using an homotopy (interpolation) between two distinct controllers. The authors followed up by developing a human-human experiment to lift a table, in which a probabilistic framework based on a gaussian mixture model showed how the robot should act as a pure leader and as a pure follower by looking at the robot force and velocity at the EEF. Then, the authors used a Gaussian mixture regression to apply the homotopy between both extremes into the homotopy controller for the robot (Evrard et al., 2009). However, the reproduction of the task did not seem to be in agreement with the human-human dyads.

In Li et al. (2015a) the authors approach the problem by modeling it as a two player game (human and robot as players). Then, a role adaptation law based on game theory is implemented.

Whitsell and Artemiadis (2017) introduced the concept of asymmetric collaboration, where the leader/follower roles could be independently exchanged in 6 degrees of freedom. The human would be needed to correct the EEF trajectory, and the robot change from leader to follower in the required degrees of freedom. Instead of an interpolation-like strategy from leader to follower boundaries, they used three different states: robot as leader; robot as follower; and an intermediate state.

In this work, we aim to allow a robot to continuously change its behavior from leader to follower when executing a task, more specifically when co-manipulating a shared object with a human partner (in a human-robot dyad).

The role adaptation is based solely on a single continuous and smooth scalar parameter  $\alpha(t)$ , which can be derived from human feedback signals, such as human arm configuration, human arm endpoint pose, arm manipulability measures, or muscle activity signals from sEMG sensors, for example.

Hereafter, the paper is organized as follows. Section 2 delves into the admittance controller design, and how to obtain a profile of varying stiffness guaranteed to have global asymptotic stability. Section 3 verifies the controller through numerical simulations of a human-robot dyad comanipulating an object, where the robot is a generic 3 DOF robot. Section 4 describes a similar simulation to the one in section 3, but with a Baxter robot simulated in a physics engine. Section 5 discusses the simulations' results. And section 6 concludes the paper and lists possible lines of future work.

# 2 Controller Design

Inspired by the stiffness variation with respect to the change in role assignments observed in the related work mentioned in section 1, here, we propose a continuously differentiable scalar role factor  $\alpha(t) \in [0,1] \quad \forall t \geq 0$  such that  $\alpha = 0$  assigns to the robot a total leader desired stiffness,  $\alpha = 1$  assigns to the robot a total follower stiffness, and the condition  $0 < \alpha < 1$  assigns mid value stiffness, *i.e.*:

Robot Role Behavior : 
$$\begin{cases} \alpha(t) = 0, & \text{Leader} \\ \alpha(t) = 1, & \text{Follower} \\ 0 < \alpha(t) < 1, & \text{Mixed} \end{cases}$$
(1)

,

The purpose of the role factor  $\alpha(t)$  is to define a role to the robot. The role can be defined in different ways, for example, from a manipulability measure, or any metric for intention of motion from the human partner in the HR dyad.

Now, let the robot end-effector (EEF) real position<sup>1</sup> be  $x_e(t)$ , and the desired robot trajectory be described by  $x_r(t), \dot{x}_r(t), \ddot{x}_r(t)$ , then the robot position error is defined as:

$$e_r(t) := x_e(t) - x_r(t)$$
 (2)

Even though for most case scenarios it is not possible to know the human desired trajectory,  $x_h(t)$ , the human position error is defined as:

$$e_h(t) := x_e(t) - x_h(t)$$
 (3)

The desired robot behavior defined by (1) aims a total leader behavior characterized by:

$$\lim_{t \to \infty} e_r(t) = 0 \tag{4}$$

and the total follower behavior characterized by:

$$\lim_{t \to \infty} e_h(t) = 0 \tag{5}$$

Let the robot equation of motion in the operational space be:

$$\Lambda(q)\ddot{x}_e + \mu(q,\dot{q})\dot{x}_e + F_q(q) = F_h \tag{6}$$

where  $q \in \mathbb{R}^n$ , is the configuration of a robot with n joints,  $\Lambda(q) \in \mathbb{R}^{3 \times 3}$  is the EEF apparent inertia matrix,  $\mu \dot{x}_e$  represents the forces at the EEF correspondent to the Coriolis matrix in joint space,  $F_g$  the force at the EEF correspondent to the gravitational torques, and  $F_h$  is the force applied by the human at the robot EEF.

In order to implement (1), we choose to use an admittance control scheme similar to the one used in Li et al. (2015b), where the admittance model possess a varying desired stiffness profile, *i.e*:

$$\Lambda_d \ddot{e}_r(t) + D_d \dot{e}_r(t) + K_d(t) e_r(t) = F_h(t) \qquad (7)$$

where  $\Lambda_d \in \mathbb{R}^{3\times 3}$ ,  $D_d \in \mathbb{R}^{3\times 3}$ ,  $K_d(t) \in \mathbb{R}^{3\times 3}$  are the desired inertia, damping, and stiffness matrices, such that all of them are positive definite and symmetric for all  $t \geq 0$ .

Then, we propose a varying stiffness profile dependent on  $\alpha(t)$  (fig. 1):

$$K_d(t) = K_{d0}(1 - \alpha(t)) + K_{d1}$$
(8)

where  $K_{d1} \in \mathbb{R}^{3\times3}$  is the minimum robot stiffness matrix, and  $K_{d0} \in \mathbb{R}^{3\times3}$  bounds the maximum robot stiffness. Furthermore,  $K_{d0}, K_{d1}$  stiffness matrices are known to produce very stiff, and very compliant behaviors respectively. In order to implement (7) with an admittance controller block,  $e_r$  is substituted by  $(x_{ref} - x_r)$ :

$$\Lambda_d(\ddot{x}_{ref} - \ddot{x}_r) + D_d(\dot{x}_{ref} - \dot{x}_r) + K_d(t)(x_{ref} - x_r) = F_h(t) \quad (9)$$

and the internal kinematic controller, is given by:

$$\dot{q} = J^{\dagger}(\dot{x}_{ref} - K_p \left(x_e - x_{ref}\right)) \tag{10}$$

 $<sup>^1\</sup>mathrm{The}$  task here is described by its position only, without considerations on orientation



Figure 1: Adaptive admittance controller with human in the loop

#### 2.1 Stability Analysis

The impedance model in (7) is guaranteed to be globally asymptotically stable only if the desired stiffness, apparent inertia, and damping matrices are constant, symmetrical, and positive definite. However, in this chapter a varying desired stiffness profile was proposed, so other stability conditions for the system in (7) must be found.

In Kronander and Billard (2016), the authors proposed a method to verify stability of mechanical impedance relationships with varying stiffness and damping. Their method is based on the following theorem, adapted here to analyze impedance in the operational space:

**Theorem 1** Let  $\Lambda_d$  be a constant, symmetric, and positive definite matrix, and  $K_d(t), D_d(t)$  be symmetric, positive definite, and continuously differentiable varying stiffness and damping profiles. Then, the system in eq. (7) with varying stiffness and damping profiles and with  $F_h = 0$  is globally asymptotically stable if there exists a  $\gamma \in \mathbb{R}^+$ , such that  $\forall t \geq 0$ :

- 1.  $\gamma \Lambda_d D_d(t)$  is negative definite;
- 2.  $\dot{K}_d(t) + \gamma \dot{D}_d(t) 2\gamma K_d(t)$  is negative definite

## **Proof:** see Kronander and Billard (2016).

In this work, only the desired stiffness profile varies with time, hence, the global asymptotic stability conditions become:

$$\gamma \Lambda_d - D_d(t) < 0 \tag{11}$$

$$\dot{K}_d(t) - 2\gamma K_d(t) < 0 \tag{12}$$

Based on the method proposed in (Kronander and Billard, 2016),  $\gamma$  is chosen to satisfy (11) such that:

$$\gamma = \min\left(\frac{\lambda_{\min}(D_d)}{\lambda_{MAX}(\Lambda_d)}\right) - 1 \tag{13}$$

where  $\lambda_{min}(\cdot), \lambda_{MAX}(\cdot)$  are the minimum and maximum eigenvalue operators respectively.

After having determined  $\gamma$ , the profile stiffness (8) has to conform to the condition (12) throughout the whole task, which may by verified through simulations, and in addition, also requires  $\alpha(t)$  to be continuous and smooth.

# 3 3R Robot Simulations

A human-robot simulation partly inspired by the work in Li et al. (2015a) is devised in which a contact between the human and the robot is expected at the robot EEF. The robot trajectory,  $x_r(t)$ , and the human trajectory,  $x_h(t)$  diverge in certain periods. Moreover, both trajectories are known a*priori*. This emulates situations when the robot is executing a task, but it is not fully aware of its environment and possible obstacles. In this scenario, the human partner would allow the robot to take the leadership of the task while the robot desired trajectory is correct in the eyes of the human, but as soon as the robot desired trajectory becomes problematic for any reason (poor trajectory execution, sudden appearance of obstacles, etc.) the human partner takes the leadership of the task by increasing his/her arm endpoint stiffness.

## 3.1 Desired Trajectories

Similarly to (Li et al., 2015a), the robot trajectory is defined as a circular trajectory in the  $\vec{x}_b, \vec{y}_b$  plane of the orthogonal frame  $\mathcal{F}_b$  placed at the robot base, and it is given by:

$$x_r(t) = \begin{bmatrix} 0.1\cos(\omega_0 t + \pi/2) \\ 0.4 + 0.1\sin(\omega_0 t) \end{bmatrix}$$
(14)

where  $\omega_0 = \frac{2\pi}{10}$ , and the robot trajectory period is 10 s. Meanwhile, the human desired trajectory is given by:

$$x_{h}(t) = \begin{cases} x_{r}(t), & t < 1.25\\ (t - 1.25)\frac{p_{2} - p_{1}}{1.25} + p_{1}, & 1.25 \le t < 2.5\\ (t - 2.5)\frac{p_{3} - p_{2}}{1.25} + p_{2}, & 2.5 \le t < 3.75\\ (t - 3.75)\frac{p_{4} - p_{3}}{2.5} + p_{3}, & 3.75 \le t < 6.25\\ x_{r}(t), & 6.25 \le t < 10 \end{cases}$$
(15)

where  $p_1 = x_r(1.25)$ ,  $p_2 = [-0.15; 0.4]^{\top}$ ,  $p_3 = x_r(3.75)$ , and  $p_4 = x_r(6.25)$  are fixed reference points. And the human trajectory ends at the same time as the robot trajectory.

It is important to note that in this work the human desired trajectory is known, which is not the case for the great majority of applications, but it allows an appropriate assessment of the roleswitching capabilities of the controller.

#### 3.2 Simulated Human Force

Authors	$K_h\left(\frac{N}{m}\right)$
(Tsumugiwa et al., 2002)	2400
(Duchaine and Gosselin, 2008)	5587
(Campeau-Lecours et al., 2016)	550
(Ott et al., 2010)	3200
(Ficuciello et al., 2015)	200

Table 1: Human endpoint stiffness values, estimated, or measured in literature

It is hard to simulate perfectly the human natural behavior analytically, but with the purpose of an analytical analysis, the human force,  $F_h(t)$ is considered here to be based on the role factor  $\alpha(t)$ . Furthermore, assuming that every human agent has its own desired trajectory for manipulation tasks, the force that the human applies at the robot EEF is similar to a spring with an equilibrium point at the human desired trajectory:

$$F_h(t) = -K_h(t)e_h(t) \tag{16}$$

where the human stiffness is proportional to the role factor  $\alpha$ :

$$K_h(t) = \alpha(t) K_{h0} \tag{17}$$

Based on the average of the impedance values for the human endpoint stiffness found in literature (table 1), a value for the maximum arm endpoint stiffness is defined as:  $K_{h0} = 2000I_2$ , where  $I_2 \in \mathbb{R}^{2 \times 2}$  is the identity matrix.

#### 3.3 Role Factor Definition

In this work, to evaluate, and illustrate the scalar role factor  $\alpha(t)$ , we define it with a sigmoid activation function that is based on the norm of the human desired trajectory error, which for this simulation is:

$$\alpha(t) = \frac{1}{1 + exp(-(600 ||e_h(t)||) - 6)}$$
(18)

Note that according to (18) if  $e_h = 0$  then  $\alpha = 0$  (robot as a leader), and for large values of  $e_h$  the  $\alpha$  value will approach 1 (robot as a follower). In addition, the use of the sigmoid activation function guarantees that the role factor is smooth if  $e_h$  is smooth as well.

## 3.4 Robot and Controller Description

The robot used is a planar robot with 3 revolution joints and the robot desired stiffness was defined by trial and error so that the robot complies with the stability condition in (12), and to obtain fast and precise tracking of  $x_h(t)$ :

$$K_d = \begin{bmatrix} k_x & 0\\ 0 & k_y \end{bmatrix} = 1000I_2(1 - \alpha(t)) + 10I_2 \quad (19)$$

The following desired apparent inertia, and damping matrices are also chosen by trial and error in such a way that it satisfies the stability condition (12) :  $\Lambda_d = 2I_2$ ;  $D_d = 32I_2$ .

The kinematic controller used by the robot (10) has  $K_p = 50I_2$ .

# 3.5 Results



Figure 2: Trajectories in a simulated HR comanipulation with a 3R robot and role adaptive admittance control.



Figure 3: Role factor variation in 3R robot simulation

The role adaptive admittance control strategy brings the robot EEF towards the human desired trajectory whenever the robot and the human desired trajectory diverge (fig. 2). Furthermore, given a smooth variation of  $\alpha$  in time (fig. 3), the transition between  $x_r$ , and  $x_h$  is also smooth. However, if the transitions are not fast enough, then the human desired trajectory error,  $e_h$  presents local maximum values during the transition (fig. 4).

Obtaining  $\gamma$  from (13), the stability condition (12) is verified for the entire simulation (fig. 5). It is noted that (12) is always true, which according to theorem 1 is a sufficient condition for the global



Figure 4: Human, and robot position error norms in 3R robot simulation



Figure 5: Terms from stability condition (12) during simulation execution

asymptotic stability of the equilibrium point in (7).

# 4 Baxter Robot Simulation

To further evaluate the variation stiffness profile proposed by (8), we implement a similar simulation to the one in section 3, but now with the Baxter robot (Rethink Robotics) in the manufacturer's simulation environment that also takes into account the Baxter robot dynamics (6). Therefore, the results from this simulation are closer to a real experiment than the results from the simulation in section 3.

# 4.1 Baxter Description

The Baxter robot has 7-DoF per arm. Each arm has torque, velocity, and position sensors for each joint. In this work, only the left arm of the robot is used. Furthermore, the manufacturer provides software for the robot simulation (fig. 6) alongside the open-source Robot Operating System (ROS) (Quigley et al., 2009), and the physics simulator Gazebo (Koenig and Howard, 2004).



Figure 6: Baxter robot in Gazebo/ROS simulation

#### 4.2 Desired Trajectories

For this simulation, the desired trajectories are redefined so that the kinematic controller (10) does not require to get close to the Baxter singularity configurations, or to its joint limits, *i.e.*:

$$x_r(t) = \begin{bmatrix} 0.7 + 0.05\cos(\omega_0 t) \\ 0.25 + 0.05\sin(\omega_0 t) \\ 0.15 \end{bmatrix}$$
(20)

where  $\omega_0 = \frac{2\pi}{30}$ , and the robot trajectory period is 30 s. Meanwhile, the human desired trajectory is given by:

$$x_{h}(t) = \begin{cases} x_{r}(t), & t < 3.75\\ (t-3.75)\frac{p_{2}-p_{1}}{3.75} + p_{1}, & 3.75 \le t < 7.5\\ (t-7.5)\frac{p_{3}-p_{2}}{3.75} + p_{2}, & 7.5 \le t < 11.25\\ (t-11.25)\frac{p_{4}-p_{3}}{7.5} + p_{3}, & 11.25 \le t < 18.75\\ x_{r}(t), & 18.75 \le t < 30 \end{cases}$$

where  $p_1 = x_r(3.75)$ ,  $p_2 = [0.7; 0.325; 0.15]^{\top}$ ,  $p_3 = x_r(11.25)$ , and  $p_4 = x_r(18.75)$  are fixed reference points. And as in the last simulation the human trajectory ends at the same time as the robot trajectory.

# 4.3 Role Factor Definition

Since the desired trajectories are redefined, the role factor definition is also redefined to produce high levels of activation in the appropriate periods of time:

$$\alpha(t) = \frac{1}{1 + exp(-(2000 ||e_h(t)||) - 6)}$$
(22)

## 4.4 Simulation Parameters

For the Baxter robot the desired admittance parameters are defined as:  $\Lambda_d = 6I_3$ ;  $D_d = 200I_3$ ;  $K_{d0} = 800I_3$ ;  $K_{d1} = 10I_3$ , where  $I_3 \in \mathbb{R}^{3 \times 3}$  is the identity matrix.

The Kinematic control parameter is given by  $K_p = 50I_3$ .

Additionally, the maximum human stiffness is  $K_{h0} = 400I_3$ , which is also within the limits of human arm stiffness values in table 1.

#### 4.5 Results

In this simulation, the role factor variation in time is not smooth (fig. 8), as it suffers from noise throughout the entire simulation execution inside Gazebo, that takes into account the robot dynamic equation of motion. This causes some noise in the human desired trajectory tracking, but most of all, the human desired trajectory error,  $e_h$ , (9) shows that when  $x_h$ , and  $x_r$  diverge,  $x_e$  does not track  $x_e$  at any period of time (fig. 7).

Furthermore, The noisy  $\alpha$  also implies that condition (12) can not be fulfilled, as the smoothness of the time-varying stiffness profile is a requisite to apply theorem 1.



Figure 7: Trajectories in a simulated HR comanipulation with a Baxter robot and role adaptive admittance control.



Figure 8: Role factor variation in Baxter simulation

#### 5 Discussion

The first numerical simulation, with the 3R robot, showcased the controller's ability to continuously



Figure 9: Human, and robot position error norms in Baxter robot simulation

adapt the role of the robot with success. However, slow rates of activation for the role factor produced undesired trajectories during role transitions from/to total leader/total follower.

The second simulation, executed with the Baxter robot simulated in the Gazebo physics engine, presented noisy values of  $\alpha$  due to its definition based on the norm of  $e_h$  (22). Because of the noisy  $\alpha$ , the robot never constantly reached the role of total follower, therefore, whenever  $x_r$ , and  $x_h$  diverged,  $e_h$  was never null. On the other hand, despite the  $\alpha$  variation, the EEF trajectory suffered only a few oscillations, this was mostly due to the fact that the desired damping and apparent inertia were chosen larger values than the ones in the first simulation.

#### 6 Conclusions

The role adaptive admittance control presented here is able to continuously switch the role of the robot from leader to follower and vice-versa, but it depends highly on the choice of the role factor  $\alpha$  adaptation to have more efficient role switching, and therefore, better human desired trajectory tracking. On the other hand, the second simulation showed that the constant parameters in the admittance model may compensate noise in  $\alpha$ , producing stable trajectories.

This work should be followed with real human-robot experiments, and careful investigations about the choice of  $\alpha$ . Furthermore, our current approach lacks considerations regarding the direction and communication of the desired movement between the agents in a dyad, which have been suggested in Mojtahedi et al. (2017) to be linked with directional stiffness adaptation, which should be another focus point of this research in the near future.

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