Human-Robot Role Arbitration with Cooperative Game Theory

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***Abstract*—This work studies the role-arbitration between a robot and a human during physical Human-Robot Interaction. The system is modeled as a Cartesian impedance, with the human and the robot interacting by applying two separate external forces. A reformulation of the problem as a Cooperative Differential Game allows addressing the bargaining problem by proposing a solution depending on the human interaction force, interpreted as the will to lead or follow. This defines the arbitration law and assigns the role of leader or follower to the robot. Experiments show the feasibility and capabilities of the proposed control in managing the human-robot arbitration during a shared-trajectory following task.**

***Index Terms*—physical Human-Robot Interaction, Role Arbitration, Cooperative Differential Game Theory, Adaptive Control, Impedance Control**

I. Introduction

With the large spread of collaborative robots, collaborative applications involving a human operator and a robot working together to achieve a common goal represents the industry's most recent trend. In contrast to coexistence (when the human and the robot are in the same environment but do not interact), synchronization (when they work in the same workspace, but at different times) and cooperation (when they work in the same workspace at the same time, though each focuses on separate tasks), collaboration happens when the human operator and the robot must execute a task together, and the action of the one has immediate consequences on the other [1]. Collaboration requires communication, which typically happens through interaction forces, leading to physical Human-Robot Interaction (pHRI) [2]. In the case the human and the robot can have complementary roles, Human-Robot Role Arbitration defines the mechanism that assigns task control to either the human or the robot [3]. As discussed in [4], game theory provides useful tools to analyze complex interactive behaviors involving multiple agents. It provides mathematical models (cooperative, noncooperative, multi-stages, etc.) of strategic interaction among rational decision-makers and provides the players with "optimal" policies to minimize their objectives, taking into account interaction. In [5], [6], and similarly, in [7], for the shared control with an exoskeleton, the continuous role adaptation is investigated for a Differential Non-Cooperative game. In these works, the concept of Nash Equilibrium is used to update the robot cost function according to the interaction force. Finally, a general framework for differential game-theoretic modeling of Human-Robot interaction is presented in [8] for the two agents game and extended to multiple agents in [9]. The previous works show that a game-theoretic description of the human-robot interaction can provide optimal behavior in a non-cooperative framework. Despite this, Nash equilibria (i.e. the solutions of the non-cooperative games) are frequently not Pareto optimal. Thus, cooperation can often improve payoffs to all players [10]. Hence, in this work, Cooperative Game Theory (CGT) is used to describe the interaction model, and Pareto solutions are sought. Cooperation, indeed, can improve the cost of each agent by agreeing. This work briefly presents the method introduced in [11]. Please refer to it for full equations derivation and a deeper work description.

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II. Method

This section presents the methodology adopted in this work to model the system, the interaction and the solution.

A. Cooperative game theoretic system modeling

Working in the Cartesian space is more intuitive and natural for the human operator; hence the desired robot motion at the end-effector is implemented as an impedance model in the Cartesian space.

$$M_i\,\ddot{x}(t) + D_i\,\dot{x}(t) + K_i\,(x - x_0)(t) = u_h(t) + u_r(t) \quad (1)$$

The system is then reformulated in a classical linear state-space formulation for integration with the Game Theoretic framework, resulting in

$$\dot{z} = Az + B_h u_h + B_r u_r = Az + B_{GT} u_{GT} \quad (2)$$

with $B_{gt} = [B_h,\ B_r]$, and $u_{GT} = [u_h, u_r]^T$, and $z = [p, v]^T$ the state vector containing positions and velocities.

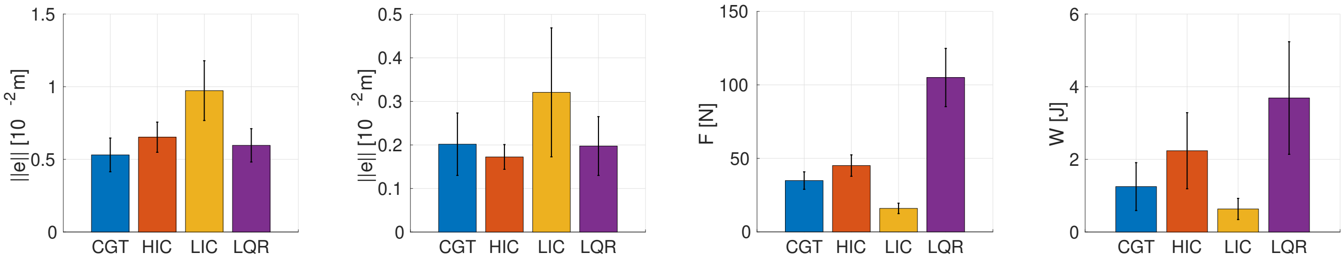
For the game-theoretic formulation, the human and the robot are assumed to minimize a quadratic cost function on the state and on the control input, defined as

$$J_i = \int_0^{\infty} \left(z\,Q_i\,z + u_i\,R_i\,u_i\right)\,dt \quad (3)$$

with the subscript i=h,r identifying the human and the robot.

A shared cost function is defined, where the parameter α represents the agreement between the two.

$$J_\alpha = \alpha\,J_h + (1-\alpha)\,J_r = \int_0^{\infty} \left(z\,Q_\alpha\,z + u\,R_\alpha\,u\right)\,dt \quad (4)$$



(a) Tracking error (b) X-correlated error (c) Force (d) Mechanical work

Fig. 1: Indexes comparison

with Q_α and R_α representing weighted cost matrices. The minimization of J_α is the same as an LQR minimization, which provides the system with the optimal feedback gain matrix $K^{fb} = R_\alpha^{-1} B_{GT}^T P$ and the feedforward gain matrix defined as $K^{ff} = [K^{fb}\ I] \begin{bmatrix} A & B_{GT} \\ C & D \end{bmatrix}^{-1} \begin{bmatrix} 0 \\ I \end{bmatrix}$.

The control input is computed as

$$u_{GT} = u^{fb} + u^{ff} = -K^{fb} z(t) + K^{ff} z_{ref}(t) \qquad (5)$$

and finally, to obtain the robot control input take the bottom rows of (5). Note that the gain matrices multiply positions and velocities, the robot contribution can be seen as additional stiffness and damping to the system in (1), leading the system to a variable impedance control.

B. Bargaining solution

In a cooperative environment, there are infinite Pareto optimal solutions and the bargaining theory addresses which is the most effective one. The bargaining problem is how to define the appropriate α. In this work, the two players bargain on who leads and follows the task; in this sense, one can accept a higher cost if he is the follower. Hence, α is used as a weighting factor to move the control authority from the robot to the human and vice-versa. Each situation in between represents a cooperative solution where the control authority is shared appropriately. The selection of the weight parameter α depends on the force applied by the human and is processed by the sigmoid function:

$$\alpha = d - \frac{a}{1 + e^{-b(||u_h|| - c)}} \qquad (6)$$

where the constant parameters a, b, c, d are used to shape the function properly.

III. Experiments

An experiment is designed to test the proposed control method for sharing control authority in human-robot collaboration. The robot has to follow a planar circular trajectory, while the human has a different path to follow, which partially overlaps with the robot one. The presented control is compared with other three similar controllers, High stiffness Impedance Controller (HIC), Low stiffness Impedance Controller (LIC), and LQR impedance controller. Table I shows the mass, spring,

TABLE I: The mass, spring and damping parameters used for the experiments.

	CGT	HIC	LIC	LQR
K	$55 \div 550$	100	20	222
D	$53 \div 135$	57	25.5	84
D/D_{cr}	$1.13 \div 0.92$	0.9	0.9	0.89
M	10	10	10	10

and damping values used. Note that spring and damping vary according to interaction, so a range is shown. It is interesting to observe that the damping ratio varies from values lower to greater than 1, allowing fast tracking with robot leading, and high damping with human leading. Four indices are evaluated for comparison: (i) trajectory following error: which measures the quality of tracking the human reference trajectory, (ii) path tracking following error: which measures the capacity to follow the geometrical path, (iii) measured interaction force: measures the force required by the human to follow its target trajectory, and (iv) mechanical work: measures the energy required by the human to follow its target trajectory. Figure 1 shows the results as the mean and standard deviation of the measured indexes for the four controllers. Despite the CGT controller is not the best one in all the cases, it can be seen that it is the one that overall minimizes all indexes together. Particularly interesting is also the variable damping behavior (see table I), which switches between values above and below the critical one, allowing fast motion when the robot is leading, and damped motion when the human is.

IV. Conclusions

In conclusion, the proposed framework shows good capabilities in describing a human-robot cooperative task. It allows easy integration of different modules (human cost function identification, human intention identification) and easy implementation of different robot behaviors (leader-follower adaptation, co-manipulation, co-transportation), which will be investigated in future works. Finally, such an approach will be extended to the cooperative human-robot transportation of carbon fiber plies and implemented in the context of the EU project DrapeBot.

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